frontiers | Frontiers in Sustainable Cities

TYPE Original Research
PUBLISHED 28 April 2025
DOI 10.3389/frsc.2025.1561308

OPEN ACCESS

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RECEIVED 15 January 2025
ACCEPTED 07 April 2025
PUBLISHED 28 April 2025

CITATION
Fan X and Xu S (2025) Does city-county merger improve urban carbon emission efficiency? An empirical analysis based on the difference-in-differences model.
Front. Sustain. Cities 7:1561308.
doi: 10.3389/frsc.2025.1561308

Does city-county merger improve urban carbon emission efficiency? An empirical analysis based on the difference-in-differences model

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The enhancement of carbon emission efficiency (CEE) in urban areas is essential for alleviating the negative impacts of climate change and promoting sustainable urban development. Nonetheless, there is no evidence to suggest that any specific spatial optimization technique significantly impacts urban spatial structure and CEE. The administrative boundary adjustment (ABA) functions as an effective instrument for hierarchical network governance in China, possessing the capacity to accomplish this objective through its redistributive impact on urban spatial resources. Thus, we utilize the "City-County Merger" (CCM)–a standard ABA policy to investigate its environmental impacts based on the mediation mechanism of urban spatial structure. The empirical findings derived from a panel dataset encompassing 285 Chinese cities and the Difference-in-Differences model (DID) indicate that the CCM will significantly enhance the CEE of urban regions. This effect is particularly pronounced in mid-western, northwestern, lower administrative level, and non-resource-based cities. The mediation mechanisms suggest that the environmental benefits of CCM in China arise from the optimization of urban spatial organization, which enhances CEE by fostering urban polycentricity and compactness. The supplementary spatial econometric analysis results demonstrate that implementing the CCM policy has a significant spatial spillover effect on the enhancement of CEE.

KEYWORDS

city-county merger, carbon emission efficiency, urban polycentricity, urban compactness, DID model

Introduction

In recent years, anthropogenic greenhouse gas emissions have contributed to global climate change and numerous adverse effects (Rosa and Dietz, 2012; Yan and Sun, 2021), seriously threatening the survival of human beings (Clark et al., 2016; Huang et al., 2021a; Li et al., 2021; Liang et al., 2019). Carbon dioxide (CO_2) emissions resulting from anthropogenic activities and fossil fuel combustion have escalated from 0.4 billion to 220 billion tons per year (IPCC, 2014; Purohit and Höglund-Isaksson, 2017; Sun et al., 2020), establishing themselves as the principal driver of global warming (Gokmenoglu and Taspinar, 2016; Li et al., 2021; Liu et al., 2021). The estimate released by the International Energy Agency (IEA) in 2021 suggests that the global average temperature is anticipated to rise by 2.6 degrees Celsius by the end of the 21st century. Consequently, the reduction of greenhouse gases and the mitigation of global climate change have emerged as a collective problem for humanity. China, the largest developing nation, has embarked on a phase of neglecting resource limitations and vigorously advancing energy-intensive and polluting heavy chemical industries (Crompton and Wu, 2005; Zhang, 2020), which has substantially augmented CO_2 emissions. According to the IEA, China's greenhouse gas emissions in 2023 amounted to 12.6 billion tons of carbon dioxide equivalent, representing a 4.13% increase from 12.1 billion tons in 2022. While China remains at the forefront globally in terms of new clean energy development, it is also one of the largest carbon emitters in the world. To address climate change, China has pledged to achieve carbon peak by 2030 and endeavor to attain carbon neutrality by 2060. The realization of the "carbon peak" and "carbon neutrality" objectives entails transitioning China's economic development model, which is currently associated with high carbon emissions, toward a low-carbon economy. This transition also requires decoupling economic growth from carbon emissions. However, achieving these goals remains a significant challenge for China.

China, since the Economic Reform and Opening Up, has changed dramatically, and the scenario in which most Chinese inhabitants resided in rural areas has entirely altered (Zhang and Song, 2003; Zhang et al., 2018), with the urbanization rate increasing from 17.9 to 63.89% (Chen et al., 2013), the number of cities ascending from 193 to 661 (Chen and Song, 2014; Tao et al., 2019), and the urban permanent population rising from 170 million to 901.99 million in China (Wang and Yeh, 2020). The proliferation of urban sprawl and expansion (Rao et al., 2020; Yue et al., 2013) has intensified various urban maladies (Ouyang et al., 2021; Ping et al., 2020), such as disorganized urban development, overpopulation, and significant traffic congestion, in addition to escalating energy consumption and greenhouse gas emissions (Abbasi et al., 2020; Yu and Zhang, 2022). 2014 IEA research indicates that urban areas, which account for 75% of global energy consumption, are responsible for nearly 80% of worldwide CO_2 emissions (Khanna et al., 2014) and have emerged as the principal source of greenhouse gases due to urbanization (Hong et al., 2021). Furthermore, as industrialization progresses and the coal-centric energy consumption framework remains largely unchanged (Dong et al., 2021; Zeng et al., 2021). China's energy demand is poised to escalate in future developmental phases (Huang et al., 2020), thereby sustaining elevated carbon emissions (Zhang et al., 2020). Consequently, enhancing carbon emission efficiency (CEE) in regions, especially urban areas, through the optimization of industrial structures, augmentation of energy efficiency, and advancement of green technology has become an imperative for China to achieve its climate objectives and adhere to international agreements mandating low-carbon development (Li and Cheng, 2020; Meng et al., 2016; Song et al., 2016).

In a free market economy, market forces predominantly drive urbanization (Jiang and Lin, 2021; Wu et al., 2007), which is perceived as a spontaneous and self-sustaining process that occurs simultaneously with industrialization. In China, the administrative boundary adjustment (ABA) has consistently served as a crucial policy instrument implemented by the government to facilitate urbanization and marketization. Particularly within the context of ongoing urbanization in China and the constrained development space in central urban areas, such adjustments have evolved into an effective means and strategic approach for urban expansion as well as urban management and governance by the Chinese government (Feng and Wang, 2021; Zeng et al., 2017; Wang and Yeh, 2020). Relevant studies indicate that the realignment of administrative divisions results in alterations to urban spatial configurations and socioeconomic conditions, including variations in fiscal revenue, redistribution of land resources, and modifications to spatial structure (Hu, 2018; Ma, 2005; Yang, 2022). Certain studies indicate that administrative restructuring substantially impacts the decentralization and centralization of territorial authority, markedly transforming urban territorial space and enhancing the urban spatial structure and form (Feng and Wang, 2021; Zeng et al., 2016; Zhou and Xu, 2020). Scholars contend that ABA would reconfigure executive authority across multiple governmental tiers, including fiscal and taxation rights, leading to substantial transformations in urban social and economic development (Chien, 2013; Gao, 2011; Lai, 2021; Liang and Zhao, 2019; Luo and Xie, 2020; Ma, 2005).

According to the relevant theories of urban spatial structure, the spatial relationship between residence and employment plays a decisive role in shaping the internal spatial structure of cities. The interaction between the land market and the labor market serves as the primary driving force behind the evolution of urban spatial structures. From this perspective, the transformation from counties to districts often results in an expansion of urban land use, which in turn determines the main direction of urban spatial expansion (Zhang et al., 2023) This process is characterized by differentiated agglomeration effects caused by intra-urban population migration and changes in population spatial distribution, thereby significantly influencing the evolution of urban spatial structures. The implementation of the ABA is expected to significantly improve urban spatial resources and production factors, thereby resulting in an increase in social and economic benefits (Tang and Hewings, 2017). Likewise, it is highly probable that the ABA would effectively tackle the issues of energy consumption and pollution connected with urbanization, while also enhancing CEE and the urban environment. The ABA can enhance urban spatial organization by promoting a compact urban form, a varied land use pattern, and a polycentric urban structure (Zhou and Xu, 2020). Optimizing the urban spatial structure enhances urban accessibility, reduces automobile dependency, upgrades the industrial framework, and disperses highly polluting enterprises (Burgalassi and Luzzati, 2015; Sun et al., 2020; Xu et al., 2019), thereby improving energy efficiency, decreasing energy consumption, and ultimately enhancing urban carbon emissions efficiency. Generally, few studies utilize ABA as a tool or approach to investigate its environmental effects through rigorous testing and mechanism elucidation. Furthermore, the mediating role of urban spatial structure is often overlooked in analyses of the relationship between policy implementation and environmental outcomes, creating an opportunity for our research. We evaluate the effects of CCM, a representative ABA strategy, on CEE and analyzed the mediation mechanisms using a DID model and robust testing methodologies.

In this study, all 285 cities in China are selected as research subjects. We utilize panel data spanning from 2003 to 2019 to investigate the relationship between CCM and CEE. The results demonstrate that CCM will significantly enhance CEE through the intermediary effect of enhancing urban spatial organization. This paper's potential contribution is twofold: theoretically, it represents the inaugural quantitative analysis of the influence of ABA on CEE through DID, offering a novel perspective and analytical approach for exploring the driving mechanisms of the urban environment; practically, the research enhances our comprehension of China's administrative strategies and furnishes robust support and justification for China's administrative reform. The subsequent structure of this essay is outlined as follows. Section 2 reviews the pertinent literature and articulates our theoretical hypothesis concerning the correlation between CCM and CEE. Section 3 addresses data sources, variable selection, and mathematical modeling. Section 4 delineates the empirical evidence and the mediating mechanism through which ABA enhances CO_2 emissions reduction. The concluding portion presents the conclusions and discussions.

Literature review and theoretical hypothesis

Numerous empirical studies have investigated the effects of national policies (Fu et al., 2021; Jiang et al., 2016; Yu and Zhang, 2021), which facilitate the execution of strategic carbon emission reduction measures. CCM serves as a crucial instrument for urban governance and management within China's urbanization process, significantly influencing the adjustment of urban spatial structure (Zhou and Xu, 2020) a vital factor impacting CEE. We examine the literature from three viewpoints and articulate our research hypothesis for the study.

CCM and CEE

Unlike Western nations, the Chinese government assumes a 'supervisory, managerial, and participatory' role during rapid urbanization (Burgalassi and Luzzati, 2015; Chung and Lam, 2004), significantly affecting China's climatic environment (Feng et al., 2022). In the early twenty-first century, to address the heightened competition among counties (Fan et al., 2012; Liu et al., 2019), the emergence of the CCM campaign has significantly influenced industrial upgrading (Deng and Pan, 2020), energy consumption restructuring (Feng et al., 2022), land use pattern transformation (Zhou and Xu, 2020), and CEE enhancement (Yu and Zhang, 2021), garnering the interest of a growing number of scholars. At now, there are mainly two viewpoints about CCM and CEE: suppression or promotion. Contrary scholars contend that the CCM will hinder advancements in enhancing CEE. Feng et al. (2022) conducted an analysis of 337 cities in China from 2013 to 2017 and found that ABA, especially CCM and CLTD (the revocation of county-level cities to urban districts) (Feng et al., 2022), leads to extensive land remising and inefficient spatial resource utilization (Zeng et al., 2016), resulting in heightened energy consumption and diminished CEE (Andong and Sajor, 2017). Moreover, several scholars argue that while residential and industrial energy consumption is expected to increase, the CEE will decline due to the expansion of industrial and construction land under the ABA (Yi et al., 2013; Zhou and Xu, 2020) The decrease in CEE, as indicated by the CCM, can primarily be attributed to resource wastage associated with the growth in land area.

Conversely, other experts assert that the CCM can improve CEE. A study of CCM and industrial structure, utilizing county-level data from Jiangsu and Zhejiang Provinces between 2000 and 2017, reveals that the implementation of reforms can positively affect the upgrading of industrial structure and enhance production efficiency through government actions, social demand, and resource availability, thereby decreasing energy consumption and fostering improvements in CEE (Zhang et al., 2017) investigates the impact of ABA on CEE, revealing that cities implementing ABA improved their urban innovation capacity and CEE. In a similar context, Feng et al. (2022) posits that government-directed administrative reorganization has the potential to significantly improve urban spatial configuration and alleviate environmental pressures in urban areas (Feng et al., 2022). Research on China's urban construction experience reveals that the implementation of CCM results in a more compact urban structure (Miyauchi et al., 2021), which significantly decreases motor vehicle travel and promotes the establishment of LCCP (Xu et al., 2019). Sun et al. (2020) argue that the CCM can establish new urban centers and enhance cities' polycentricity, often linked to reductions in carbon emissions (Sun et al., 2020).

This study argues that the expansion of urban areas resulting from CCM will generate scale and agglomeration effects, thereby facilitating the movement of production factors and attracting talent, technology, and capital to urban regions (Tang and Hewings, 2017). The scale and agglomeration effects are expected to enhance urban production efficiency and foster innovation, thereby offsetting the land resource wastage and reduced CEE associated with the urban expansion of the CCM. Conversely, during the execution of the CCM strategy, both central and local governments may alter the urban spatial configuration chiefly via territorial and political powers (Feng and Wang, 2021; Zeng et al., 2016; Zhou and Xu, 2020). Optimizing and upgrading urban spatial structures will reorganize production elements and enhance production processes, leading to reduced energy consumption and improved CEE (Tang and Hewings, 2017; Sun et al., 2020). Consequently, the subsequent hypotheses are posited:

> *Hypothesis 1*: The implementation of CCM is expected to significantly enhance CEE.

Urban spatial structure and CEE

Cities primarily obtain their energy consumption and carbon emissions from three sectors: residential, industrial, and transportation. Furthermore, previous research has demonstrated that modifying the urban spatial organization can reduce carbon emissions and enhance efficiency. The CCM serves as an essential urban management and governance strategy, significantly influencing the optimization of urban spatial structure and enhancing CEE.

Previous studies have primarily highlighted that following the implementation of the CCM, the administrative boundaries between districts and counties become less pronounced, spatial connectivity is enhanced, and the municipal government assumes unified responsibility for the provision of public transport services, extending coverage to the former counties. This transformation is expected to enhance the integration and efficiency of public transport systems, promote the substitution of private transport, and consequently improve CEE (Liang and Zhao, 2019; Yang, 2022; Wang et al., 2011; Zhao et al., 2022). Compared with previous studies that primarily focused on spatial linkage and spatial integration, this paper systematically elaborates on the mediating role of urban spatial structure in the relationship between CCM and carbon emission efficiency from three distinct perspectives. Initially, from the viewpoint of a polycentric framework, the CCM serves as an instrument for converting counties into urban districts (Hare, 1999) and positively affects the degree of urban polycentricity, which benefits CCE in two ways. Enhancing polycentricity driven by the CCM might reduce urban commuting distances and durations in metropolitan areas, especially those exhibiting a balanced work-residence distribution, hence diminishing traffic and residential emissions. Heightened polycentricity enhances the probability that pollutants in urban regions will be dispersed over multiple sites, promoting the natural dilution of industrial carbon emissions. Therefore, we suggested the hypotheses as follows:

> *Hypothesis 2*: The CCM improves urban CEE by increasing polycentricity.

Secondly, extensive research has demonstrated that the policy of CCM serves as a strategic initiative to foster the development of compact cities. This policy ensures that the growth rate of urban land use remains significantly lower than the population growth rate, thereby helping to curb urban sprawl and consequently reducing carbon emissions. We argue that a compact urban structure can mitigate carbon emissions linked to travel and residential energy use by decreasing per capita housing area and transitioning urban transportation from private vehicles to public transit, thereby enhancing the efficiency of urban carbon emissions (Lim et al., 2019; Zhu et al., 2022). Upon the implementation of the CCM, the examination and approval authority of counties will be transferred to Chinese cities. This transition will enhance the government's capacity for regional coordination and address cross-border governance challenges in public affairs. Additionally, it will aid the government in strategizing land use planning and fostering intensive urban development, thereby mitigating urban sprawl and enhancing urban compactness. According to the preceding study, our third hypothesis is as follows:

> *Hypothesis 3*: The CCM would enhance the compactness of metropolitan areas, hence increasing CEE in cities.

Finally, according to prior research, the transformation of CMM represents a comprehensive urbanization development strategy. This policy involves transferring land approval authority from county governments to municipal governments, with the abolished counties' land use planning and management being uniformly overseen by the municipal government. As a result, the layout of urban functional zones becomes more mixed, rational, and compact, thereby enhancing CEE. The paper examines the mediating influence of land use structure on CCM and CEE. The adoption of the CCM reform will facilitate the development and construction of all categories of urban land, encompassing residential, industrial, commercial, public service, and engineering facilities. Consequently, the urban land use framework would transform, leading to an augmentation in the extent of land use integration (Zhou and Xu, 2020). As the degree of mixing increases, traffic congestion and commuting distances between employment and housing significantly decrease, which is often inversely related to traffic emissions but positively related to CEE (Yi et al., 2013). Consequently, this paper posits the subsequent assumptions:

> *Hypothesis 4*: The CCM would optimize land use structure and increase land use mixing, hence enhancing CEE.

Spatial effects of CEE

Previous studies assume that different cities operated independently of one another, without considering the extensive interconnections among cities, the flows of various production factors between them, or the potential spatial spillover effects resulting from the implementation of CMM. This study argues that the CCM serves as an essential instrument for mitigating competition among cities or counties, as it not only removes obstacles to the communication of factors such as technological innovation and human capital but also influences production factors in adjacent cities through scale diffusion effects, thereby facilitating the unrestricted movement of elements between urban areas. The elements influencing CEE, including scientific and technological resources and a highly skilled labor force, can circulate freely due to regional networking and information platforms, significantly affecting the spatial spillover effect of CEE (Feng et al., 2020; Song et al., 2020). This research presents the following hypotheses derived from the previously discussed analytical procedure:

> *Hypothesis 5*: The execution of CCM policy not only improves CEE, but also has a spatial spillover effect on adjacent cities.

Materials and methods

Model construction

Drawing on relevant research (Gao et al., 2022), this study employs a time-varying DID model to evaluate the effects of CCM policies on CEE. In this study, cities are divided into two groups. One group that implemented the CCM policy is defined as the treated group, while the other is defined as the control group. Furthermore, the STIRPAT model provides a framework for analyzing factors influencing environmental change; thus, it will be incorporated into the benchmark model (Huang et al., 2021b). To investigate the average treatment effect of CCM on CEE, Equation 1 is employed:

$$\ln CEE_{it} = \alpha + \beta treat_i * post_t + \gamma lnX_{it} + \lambda_t + u_i + \varepsilon_{it} \quad (1)$$

In this equation, CEE_{it} is the dependent variable, defined as urban CEE; $treat_i * post_t$ represents the dummy variable for CCM reform; the coefficient βquantifies the average treatment effect of CCM on CEE. X_{it} comprises a set of control variables, mostly encompassing natural environmental aspects as well as social and economic variables. $\lambda_t$represents the time fixed effect; $u_i$signifies the city fixed effect; ε_{it} symbolizes the error term.

To evaluate hypotheses H2-H4 and ascertain the precise mechanism by which CCM enhances CEE, we develop the subsequent mediating effect model Equations 2–4:

$$\ln CEE_{it} = \alpha + \beta treat_i * post_t + \gamma lnX_{it} + \lambda_t + u_i + \varepsilon_{it} \quad (2)$$

$$mediator_{it} = \alpha + \beta_1 treat_i * post_t + \gamma lnX_{it} + \lambda_t + u_i + \varepsilon_{it} \quad (3)$$

$$\ln CEE_{it} = \alpha + \beta_0' treat_i * post_t + \beta_2 mediator_{it} + \gamma lnX_{it} + \lambda_t + u_i + \varepsilon_{it} \quad (4)$$

In this equation, $mediator_{it}$ denotes the mechanism variable designed to enhance CEE, specifically referring to the urban spatial structure, which includes both polycentric and compact of cities. The definitions and interpretations of urban land use structure and other variables remain consistent with those presented in Equation 1.

The inability of administrative boundaries to contain the propagation and diffusion of CO_2 results in a notable geographical dependence in the CEE of adjacent cities, potentially skewing the estimation outcomes of this research. Consequently, in accordance with pertinent research (Feng et al., 2020; Song et al., 2020), this study, the spatial Durbin model (SDM) is employed to investigate the spatial spillover effects of CCM on CEE. Additionally, comparative analyses are conducted using the spatial autoregressive model (SAR) and the spatial error model (SEM) to evaluate their respective performances relative to CCM.

$$\ln CEE_{it} = \alpha_0 + \lambda W u_{it} + \alpha_1 treat_i * post_t + \alpha_i lnX_{it} + \varepsilon_{it} \quad (5)$$

$$\ln CEE_{it} = \alpha_0 + \rho W lnCEE_{it} + \alpha_1 treat_i * post_t + \alpha_i lnX_{it} + \varepsilon_{it} \quad (6)$$

$$\ln CEE_{it} = \alpha_0 + \rho W lnCEE_{it} + \alpha_1 treat_i * post_t + \alpha_1' W treat_i * post_t + \alpha_i lnX_{it} + \alpha_i' W lnX_{it} + \varepsilon_{it} \quad (7)$$

Equation 5 denotes the SEM model, Equation 6 signifies the SAR model, and Equation 7 illustrates the SDM model. In these equations, ρ signifies the spatial autocorrelation coefficient; λ stands for the spatial error coefficient; Wu_{it} indicates the spatial error term; $WlnCEE_{it}$ represents the spatial lag of the dependent variable; $Wtreat_i * post_t$ denotes the spatial lag of the independent variable; $WlnX_{it}$ encompasses the spatial lags of control variables. W symbolizes the spatial weight matrix constructed based on the Rook contiguity rule.

Variable selection

Dependent variable

The variable CEE, assessed using the SBM-DEA model that incorporates undesired outputs. Drawing on prior research, this study evaluates CEE by considering labor, capital, and energy as input factors, GDP as the desirable output, and CO_2 emissions as the undesirable output. Specifically, (1) The number of urban units employed at year-end serves as a proxy for labor input (Gao et al., 2022). (2) The perpetual inventory method (PIM) was utilized to estimate the capital stock of each city at constant prices, serving as a proxy for capital input (Song et al., 2020). (3) Total energy consumption, which is calculated by converting various energy sources—such as natural gas, liquefied petroleum gas, and electricity—into standard coal using established coefficients, serves as a proxy variable for energy input (Wang et al., 2019). (4) This work establishes the price index with 2003 as the base year and derives the regional real GDP as a substitute variable for predicted output (Xu et al., 2018). (5) Using the 1×1 km grid of monthly CO_2 emission data we derived urban carbon emissions as a substitute variable for the undesirable result by employing raster overlay, projection transformation, and clipping techniques (Table 1).

Independent variable

The variable $treat_i$ represents the implementation status of the CCM reform within the city during the study period. A value of 1 indicates that the CCM reform has been implemented in the city, categorizing these cities as part of the treated group. Conversely, a value of 0 signifies that these cities belong to the control group (Figure 1).

Control variables

This paper, drawing on the prior studies, incorporates several control variables and a policy dummy variable pertinent to CEE. Specifically, this study includes: (1) Population density, which serves as an indicator of demographic influence (Gao et al., 2022; Zhang et al., 2022). Areas with high population density can achieve a substantial reduction in CEE through optimized infrastructure and scale effects, particularly in the advancement of clean energy adoption and the effectiveness of policy implementation. This indicator is quantified by the number of populations per unit area of urban land, denoted as POP. (2) GDP serves as the most direct indicator of urban economic development. The enhancement of economic development is typically associated with technological advancements, industrial transformation, optimization of the energy mix, and the reinforcement of environmental policies. Collectively, these factors contribute to improving carbon emission efficiency and facilitating the transition toward low-carbon development. To account for variations in population size across different cities, per capita GDP is employed to assess the level of urban economic development (Huang et al., 2021a), which will be referred to herein as ECO. (3) Green technology innovation is a metric utilized to assess the extent of technological advancements in areas such as environmental protection, resource utilization, and energy efficiency improvement within a city. Green technology innovation has the potential to significantly enhance carbon emission efficiency through the development and promotion of clean energy, energy-saving technologies, and carbon capture methods. On one hand, renewable energy technologies such as photovoltaics and wind power directly replace fossil fuels, thereby reducing the carbon intensity per unit of output. On the other hand, advancements in smart grid systems and industrial process optimization improve energy utilization efficiency,

TABLE 1 Input and output indicator system.

Indicator type	Indicator name	Indicator meaning
Input	Labor	Quantity of Employment
	Capital	Capital Stock
	Energy	Various energy consumption (convert to standard coal)
Output	Gross regional product	GDP
	Carbon dioxide missions	Sourced from the center for global environmental research

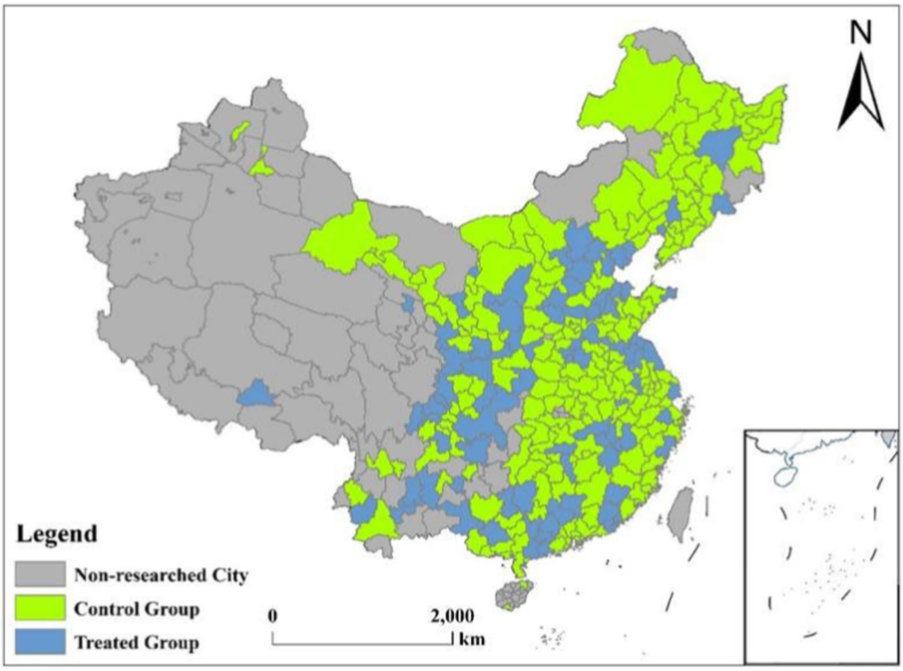

FIGURE 1
Treated group and control group.

leading to a decrease in energy consumption necessary for achieving equivalent economic output. This metric is quantified by the number of green patent applications (Zhang et al., 2022) and denoted as INOV. (4) According to the principles outlined by the environmental Kuznets curve, the relationship between urbanization levels and CEE exhibits complex nonlinear characteristics. In the initial stages of urban expansion, there is a tendency for CEE to decline due to increased energy consumption and alterations in industrial structure. However, as urban development progresses into its middle and later stages, the benefits derived from technological innovation diffusion, infrastructure sharing, and enhanced green governance capabilities—fostered by agglomeration effects—can significantly enhance CEE through economies of scale and optimization of energy systems. In this study, a composite nighttime lighting index (URB), derived from nighttime lighting data, is introduced to quantify the degree of urbanization. The calculation process is illustrated in Equation (8). Specifically, the average light intensity ($urban_1$) is utilized as an indicator to quantify the level of urbanization. The spatial extent of urbanization ($urban_2$) is assessed by measuring the illuminated area per unit of urban land. In accordance with relevant studies (Huang et al., 2021a), the parameter φ is set to 0.8. (5) The impact of opening up to the outside world on CEE is primarily manifested in the fact that trade liberalization and foreign investment can facilitate the introduction of clean technologies and the upgrading of industrial structures via technology spillover effects. This, in turn, promotes improvements in energy efficiency and the adoption of low-carbon technologies, thereby enhancing CEE. Nevertheless, international industrial relocation may result in the "pollution haven" effect, potentially increasing local carbon intensity in the short term if energy-intensive industries are introduced or environmental regulations are insufficient. The per capita foreign direct investment (FDI) is utilized to signify the level of openness (Huang et al., 2021a) in this study, referred to as OPEN. (6) The impact of industrial structure on carbon emission efficiency is primarily manifested in the varying energy consumption intensities and emission characteristics across different industrial sectors. Specifically, the secondary industry, particularly heavy industry, as an energy-intensive sector, generates substantial carbon emissions due to its high reliance on fossil fuels, thereby considerably diminishing overall carbon emission efficiency. This study utilizes the ratio of the secondary industry within GDP as a proxy variable for industrial structure (Liu et al., 2021) to assess its impact on CEE, henceforth referred to as STRU. (7) This study selects average annual temperature (TEMP), annual precipitation (RAIN), and wind velocity (WIND) as key meteorological factors to evaluate their influence on carbon emissions efficiency (CEE). It recognizes that natural factors play a significant role in the dispersion of urban carbon emissions, which subsequently affects CEE (Cai et al., 2017; Wang et al., 2021). Natural geographic factors, including average annual temperature, annual precipitation, and wind velocity, exert multi-dimensional influences on CEE by affecting ecosystem carbon sink capacity, energy consumption patterns, and renewable energy potential. Within a moderate range, higher temperatures can enhance plant photosynthesis efficiency; however, extreme high temperatures may inhibit vegetation growth and increase energy consumption for refrigeration. Adequate precipitation facilitates vegetation carbon uptake and soil carbon sequestration, whereas drought or flooding weakens carbon sequestration capabilities. Increased wind speed can promote atmospheric carbon diffusion and improve wind energy utilization, yet strong winds may accelerate soil erosion and release stored carbon pools. These factors interact with human activities to collectively shape the regional carbon cycle balance.

$$urban_i = \varphi urban_1 + (1-\varphi) urban_2 \quad (8)$$

Mechanism variables

This paper selects urban polycentricity, urban compactness, and land use mix as mediating factors to investigate the mediating effects of urban spatial structure on CCM and CEE, based on pertinent studies (Sungwon and Bumsoo, 2020; Zhu et al., 2022) and theoretical frameworks presented in Part 2.

Polycentricity denotes the extent to which the cores of a city are evenly distributed. Previous empirical studies have analyzed polycentricity from both morphological and functional viewpoints. It can be measured by urban morphological factors such as urban population, labor force, and gross regional product (GDP), together with urban functional variables like population mobility and external information exchange connections. This study evaluates urban polycentricity through population distribution to more clearly illustrate the internal spatial structure of a metropolis from a morphological standpoint (Sun et al., 2020; Zhu et al., 2022).

First, the city center is identified and extracted using 1 km × 1 km LandScan TM population data through the relative minimum threshold method. Utilizing pertinent literature, we establish 90 percent of the maximum population density of each city as the minimal criterion for identifying its cores. This research measures the polycentricity of a metropolis using a network analysis method whereby a higher number indicates increased polycentricity and a more equitable growth of the city's several centers. Equation 9 is as follows:

$$polycentricity_i = 1 - \frac{\sigma_{obs}}{\sigma_{\max}} \quad (9)$$

Where $polycentricity_i$ is the polycentricity of city, σ_{obs} is the standard deviation between the "importance" of various centers within the city, and $\sigma_{\max}$ denotes the standard deviation between the "importance" of the city's largest center and zero. In this paper, the total population of each center represents its "importance."

A compact city is distinguished by having a population density that is relatively high, a social and economic landscape that is diverse, and effective public transportation that encourages people to walk there. At present, there is a lack of consensus among professionals regarding the assessment of the compactness of metropolitan areas. It is impossible to describe the increasingly rich connotation of a compact city in the contemporary research of compact cities because compact cities are traditionally measured using a simple urban form approach, such as the ratio of the urban perimeter to the smallest circumferential circumference. This is because compact cities are measured using a simple urban form approach. With reference to previous research (Miyauchi et al., 2021; Zhu et al., 2022), the present investigation takes into account population, economics, land, and transportation in order to develop the urban compactness index system. The results of this investigation are presented in Table 2. Additionally, in order to accomplish a comprehensive analysis of the compactness of each city, we make use of the entropy method. The range normalization strategy is utilized first in order to normalize the initial data. Subsequently, the entropy method is utilized in order to ascertain the weight of each indicator. Finally, the multi-objective weighted summation method is utilized in order to compute the compactness index of each city. The calculation method for the compactness index is presented in Equation 10.

TABLE 2 Comprehensive evaluation index system of urban compactness.

	Indicator	Description
Population compactness	The population density	The number of populations per unit area of urban land
	The residential density	The ratio of population density to residential area in a municipality
Economic compactness	Per capital GDP	The ratio of the municipal district's GDP to its entire population
Land compactness	Land development intensity	The ratio of developed space to municipal area
	Land use capability	The ratio of urban development land area to built-up area
Traffic compactness	Per capita public transport	The proportion of a city's population to the number of buses in the city
	Road network density	The proportion of road length to municipal district area

$$compactness_i = \sum_{j=1}^{m} p_{ij} * w_j \quad (10)$$

Where m denotes the number of urban compactness categories. $compactness_i$ s the compactness index of city$i$, and the compactness level increases as the value increases. p_{ij} is the standardization index value of item$j$ of city i. w_j is the indicator weight.

The transformation of regional land use structure serves as a direct indicator of changes in land utilization within the region, primarily reflecting the composition of natural resources and the socioeconomic development specific to that area. This has significant implications for regional industrial organization and optimal land use practices. The degree of land use mixedness is indicative of urban land structure characteristics at a macro level and is influenced by the intrinsic nature and essence of the land use framework. The calculation methods are presented in Equations 11 and 12. The methodology for calculation is outlined as follows:

$$P_i = \frac{A_i}{A} \quad (11)$$

$$mixedness_j = -\sum_{i=1}^{N} P_i * \ln P_i / lnN \quad (12)$$

Where A represents the total urban land area, A_i denotes the land use area corresponding to the i-th category, N is the kind of urban land use, P_i reflects the proportion of various land areas relative to the total land area, and $mixedness_j$ signifies the degree of mixed urban land use in the j-th city.

Data sources

In light of the changes in administrative divisions and potential data discrepancies, this study selects 285 Chinese cities as the empirical sample from 2003 to 2019. The monthly carbon emission raster data utilized in this study are obtained from the Center for Global Environmental Research. The implementation status of the CCM policy is obtained from the Chinese Administrative Regionalization network. We employ an extended time-series dataset of nighttime light data, resembling the VIIRS format, covering the period from 2000 to 2019. This dataset has been sourced from the Harvard Dataverse. Social and economic data are obtained from the statistical yearbooks of Chinese cities. In contrast, meteorological and climatic data are sourced from the National Centers for Environmental Information of NOAA.

Empirical results

Parallel trend test

The parallel trend hypothesis serves as a fundamental prerequisite for the DID model, which is frequently utilized to evaluate the social and economic impacts of implementing CCM policy. This paper utilizes event analysis, as referenced in pertinent studies (Gao et al., 2022) to investigate the parallel trends between the treated and control groups prior to the implementation of the CCM policy. The formula is defined as follows:

$$\ln CEE_{it} = \beta_0 + \sum_{k \geq -5}^{5} \beta_k did_{i,t}^{k} + \gamma lnX_{it} + \lambda_t + u_i + \varepsilon_{it} \tag{13}$$

where the $did_{i,t}^{k}$ is the dummy variable of the CCM policy, whereas it signifies the time frame preceding and succeeding the policy's enactment. This work utilizes the five years preceding and after the policy implementation as the research period for parallel trend analysis. Figure 2 illustrates that the regression coefficients of the policy dummy variables remain close to zero and lack significance within the upper and lower 95% confidence intervals prior to the reform. This observation confirms that the prerequisite assumption of parallel trends is satisfied.

Baseline analysis results

This study conducted a stepwise regression analysis to investigate the impact of the CCM policy on urban CEE, employing a DID model as specified in Equation 1. Particular attention was given to the coefficient of $treat_i * post_t$ within the model. The first column (1) presents the estimated results, which exclusively include the independent variable in the model. Column (2) additionally accounts for characteristics including population, affluence, and technology in comparison to column (1). Based on column (2), column (3) incorporates additional social and economic variables that may affect urban carbon emission efficiency. Furthermore, column (4) introduces controls for the influence of natural environmental factors on CEE in addition to those included in column (3). It is essential to emphasize that columns (1) through (4) incorporate both city fixed effects and time fixed effects. The findings reveal that the coefficients of the dummy variables $treat_i * post_t$ in columns (1) through (4) are significantly positive at the 5% significance level. This indicates that the implementation of the CCM policy is likely to substantially enhance CEE. According to the findings in column (4), the CCM policy elevates the CEE by approximately 0.0368 in comparison to the control group. Therefore, Hypothesis 1 has been validated (Table 3).

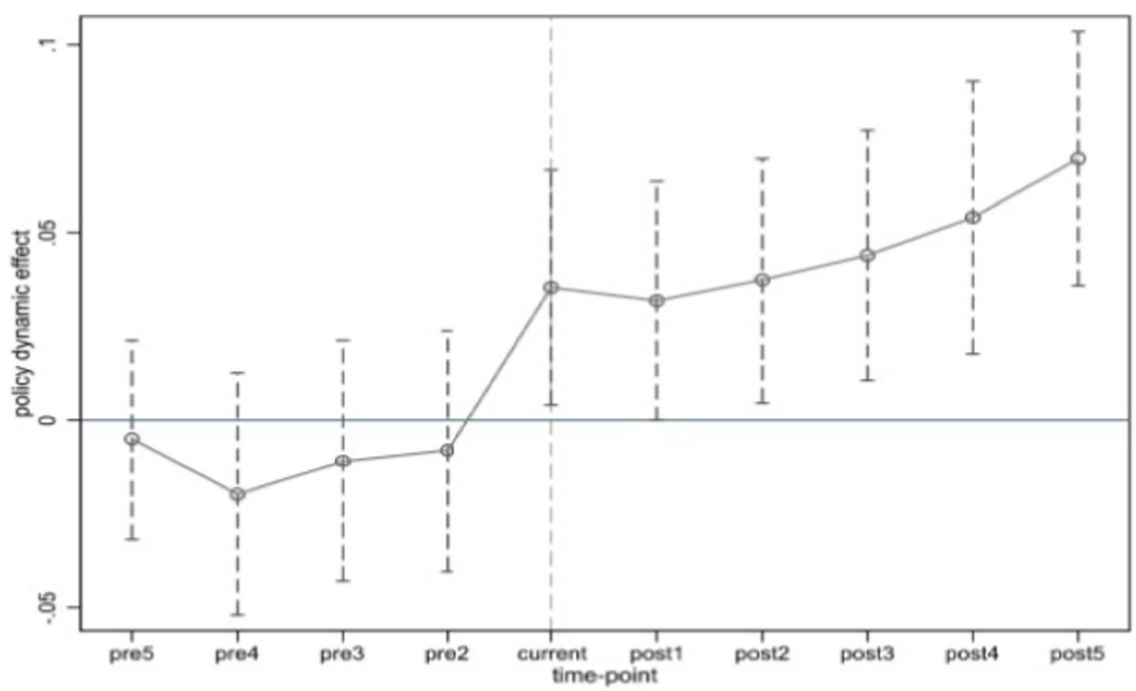

FIGURE 2
Parallel trend test of CMM policy.

Robust tests

Counterfactual analysis: placebo test

Despite the incorporation of numerous variables that influence CEE and CCM policy into the empirical model presented in this paper, the diverse characteristics of cities make it impossible to account for all factors associated with both independent and response variables, particularly those that are unobservable. This work employs the indirect placebo method (Ferrara et al., 2012) to randomly produce a list of cities implementing the CCM reform. The regression analysis was conducted 1,000 times based on the newly established treatment and control groups. Figure 3 shows that the p-values of the coefficients $\hat{\beta}^{random}$ conform to a normal distribution, with the coefficients mainly clustered around zero. This suggests that unobservable factors do not introduce bias into the baseline results, and the baseline analysis results in outcomes remain robust.

PSM-DID model

The DID model is essential for establishing causality; however, a significant challenge emerges in sample selection, as the cities adopting the CMM policy may not have been randomly chosen due to intergovernmental relations between central and local authorities, which can result in biased estimates. To address the issue of sample self-selection, we utilize PSM method to ensure that the characteristics of both the treated and control groups are as comparable as possible across all dimensions (Heckman et al., 1997). Subsequently, we re-estimate the outcomes based on this matching process. Initially, we employ the Logistic model to compute the propensity score, utilizing the control variables as covariates. Secondly, this work employs the 1:1 nearest neighbor matching technique for sample alignment and illustrates the disparities in variables before and after matching, as depicted in Figure 4 and Table 4. The findings indicate that the standard deviation of each covariate prior to sample matching exceeds that observed post-propensity matching, hence demonstrating that sample matching enhances the validity of subsequent analyses. This study utilizes the DID model to re-estimate and conduct regression analysis using matched samples.

Other policies impacting CEE

This paper investigates the impact of China's recent low carbon development policies on the CEE of urban regions by analyzing their effects on industrial structure, energy intensity, and technological advancement. It specifically focuses on two pertinent policies: LCCP policy and the CET policy [72], to ascertain whether their implementation skews the primary research conclusions. This study integrates the interaction terms $treat * post * lccp$ and $treat * post * cet$ between low carbon development policies and the CCM reform into the benchmark model, referencing pertinent studies to examine the influence of CET and LCCP policies on the primary research conclusions. The findings in columns (2) and (3) of Table 5 indicate that the coefficients of interaction terms lack both economic and statistical significance.

Additional robustness tests

To ascertain the credibility and dependability of research conclusions on CCM policy and CEE, this paper utilizes three approaches for robustness verification and offers the robust analysis results in Table 5.

First, this paper substitutes the dependent variable. It is widely recognized that improvements in CEE are generally correlated with reductions in carbon emissions. Therefore, we employ urban per capita carbon emissions as the dependent variable for this study to evaluate the robustness of CCM policies concerning CEE. Column (4) of Table 5 shows that the coefficient of the $treat_i * post_t$ is negative and

TABLE 3 Baseline analysis results of model.

Variables	(1)	(2)	(3)	(4)
	CEE			
$treat_i * post_t$	0.0480*** (3.07)	0.0401*** (2.60)	0.0377** (2.54)	0.0368** (2.48)
POP		0.403*** (4.23)	0.394*** (4.21)	0.412*** (4.40)
GDP		0.00416 (0.15)	0.0978*** (2.62)	0.0969*** (2.62)
INOV		0.0273** (2.57)	0.0314*** (2.73)	0.0321*** (2.81)
URBAN			−0.0204 (−1.08)	−0.0208 (−1.10)
FDI			−0.000520 (−0.09)	−0.000634 (−0.11)
INDUST			−0.00475** (−2.51)	−0.00474** (−2.51)
TEMP				−0.0280*** (−3.44)
RAIN				−0.0466*** (−2.68)
WIND				0.0193 (1.55)
Constant	0.667*** (34.32)	−1.707*** (−3.22)	−2.350*** (−3.99)	−1.678** (−2.40)
City effect	YES	YES	YES	YES
Time effect	YES	YES	YES	YES
R^2	0.147	0.170	0.186	0.189
N	285	285	285	285
Observations	4,845	4,845	4,845	4,845

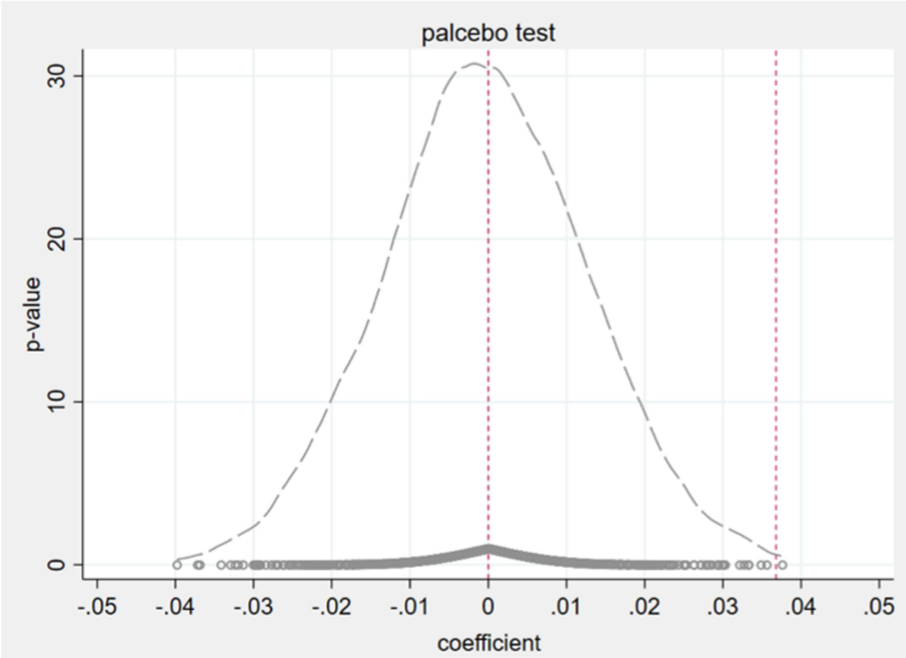

FIGURE 3
Placebo test.

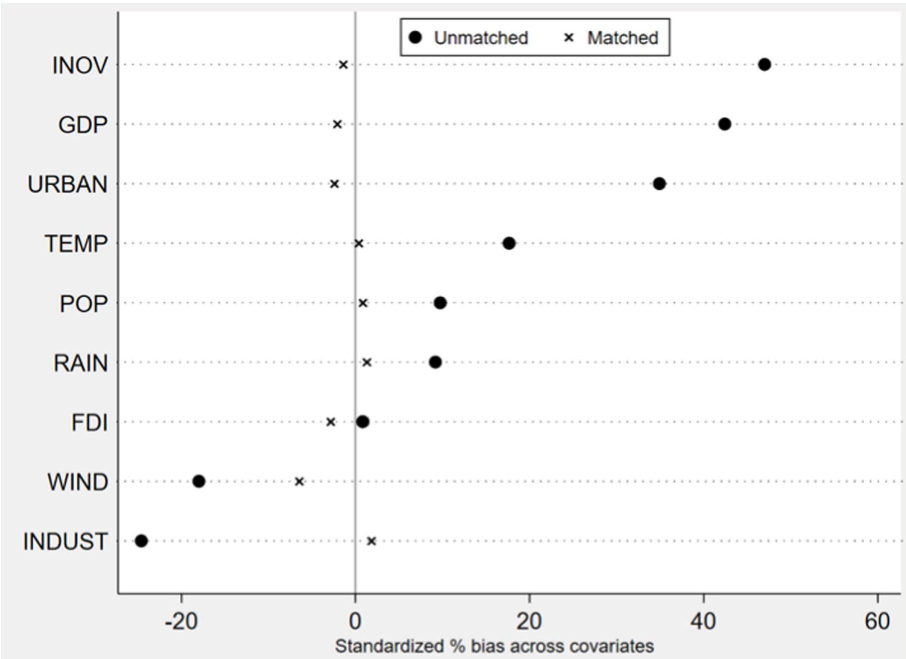

FIGURE 4
The diagram of standardization deviation before and after propensity matching.

statistically significant at the 5% levels. This finding implies that CCM policies effectively facilitate a reduction in urban carbon emissions, thereby reinforcing the robustness of our conclusions.

Secondly, this study employs GMM method to replace the OLS method. Given the potential time lag in CEE due to persistent CO_2 emissions, we utilize the second-order and higher-lag terms of CEE as instrumental variables. The SYS-GMM method is applied for dynamic panel data estimation. Column (5) of Table 5 shows that the coefficient of $treat * post$ remains positive and statistically significant at the 5% level when employing GMM method. This finding indicates that the choice of estimation techniques does not alter the study's conclusions, thereby enhancing the robustness of the results.

TABLE 4 The results of the balance test.

Variables	Unmatched / Matched	Mean: Treated	Mean: Control	Bias (%)	Reduction |bias| (%)	t-test: t	t-test: p > |t|
POP	U	5.7899	5.7008	9.7	91.3	2.22	0.027
	M	5.7899	5.7822	0.8		0.15	0.883
GDP	U	10.513	10.166	42.4	95.1	9.67	0.000
	M	10.513	10.530	−2.1		−0.37	0.710
INOV	U	4.5714	3.6549	47.0	97.0	11.42	0.000
	M	4.5714	4.5987	−1.4		−0.24	0.814
URBAN	U	−1.1177	−1.6295	34.9	93.0	7.83	0.000
	M	−1.1177	−1.0821	−2.4		−0.41	0.683
FDI	U	3.6523	3.6363	0.8	−242.2	0.20	0.844
	M	3.6523	3.7069	−2.9		−0.47	0.638
INDUST	U	45.052	47.749	−24.6	92.7	−5.61	0.000
	M	45.052	44.855	1.8		0.33	0.744
TEMP	U	15.222	14.323	17.7	97.8	4.00	0.000
	M	15.222	15.202	0.4		0.07	0.945
RAIN	U	9.1547	9.1114	9.2	86.0	2.11	0.035
	M	9.1547	9.1486	1.3		0.22	0.826
WIND	U	2.9273	3.0418	−18.0	64.1	−4.16	0.000
	M	2.9273	2.9684	−6.5		−1.12	0.264

Finally, we exclude the exceptional samples and adjusted the research scope. Given the unique political and economic status of municipalities within China's urban system, which may result in sample value polarization and biased estimation outcomes, the data from these four cities have been omitted. The reform process of China's CCM has distinct periodic characteristics, comprising the initial phase from 1997 to 2006, the subsequent phase from 2011 to 2019, and a stagnation period from 2007 to 2010. This study designates the period from 2007 to 2019 to examine the effect of CCM reform on CEE, thereby mitigating the mutual influence of policy implementation across multiple timeframes. The findings in columns (6) and (7) of Table 5 indicate that altering the study sample and range does not affect the results, hence illustrating the relative robustness of the empirical outcomes.

Heterogeneity test

Differences in economic distribution

There is a widespread consensus that significant disparities exist among the various regions of China regarding economic growth and levels of urbanization. The eastern region has been found to surpass both the central and western regions in terms of green innovation technologies, upgrading industrial structures, and enhancing energy efficiency. This work investigates significant spatial disparities in enhancing CEE through CCM policy. To achieve this objective, the study sample was categorized into three groups: cities located in the eastern, central, and western regions, followed by regression analysis. The findings in columns (1) and (2) of Table 6 indicate that CCM reform can successfully enhance urban CEE in central and western China, whereas the improvement is not significant in eastern China. This is primarily attributable to the superior technological innovation, advanced industrial framework, and elevated energy efficiency of eastern cities compared to those in the central and western regions, thereby complicating CCM reform's ability to improve CEE in eastern cities.

Differences in population distribution

As a primary contributor to energy consumption and carbon emissions, population factors significantly influence urban CEE. Significant spatial disparities exist in China's population distribution, making it essential to examine how these variances affect the relationship between the execution of CCM policy and CEE. The Aihui-Tenchong Line, developed by Hu Huanyong in 1935, illustrates the spatial distribution characteristics of China's people, significantly influencing the nation's economic configuration, transportation advancement, and environmental development. In this paper, the study sample is divided into two groups: cities located in the south-east of the HU line and cities located in the north-west of the HU line. The heterogeneity of the impact of CCM reforms on CEE is further analyzed. The data in columns (3) and (4) of Table 6 reveal that the coefficient of the interaction term for northwestern cities is significantly greater than that for southeastern cities, suggesting that the CCM policy has a more substantial impact on enhancing CEE in the northwestern regions. This primarily results from the high population density in southeastern cities, which leads to greater resource consumption and increased CO_2 emissions. Consequently, the transition of counties to urban districts may diminish urban CEE, potentially negating the improvements in CEE brought about by the CCM reform.

TABLE 5 Robustness tests.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CEE	CEE	CEE	CO_2	CEE	CEE	CEE
L.CEE					0.928*** (249.73)		
$treat_i * post_t$	0.0363*** (3.51)	0.0428** (2.06)	0.0360** (2.23)	−0.175** (−2.41)	0.0423*** (4.61)	0.0362** (2.36)	0.0250*** (2.67)
POP	0.419*** (9.01)	0.408*** (4.28)	0.343*** (3.56)	−1.226 (−1.17)	−0.0358*** (−6.34)	0.411*** (4.37)	0.2790*** (4.15)
GDP	0.103*** (6.08)	0.0969*** (2.63)	0.101*** (2.80)	0.2010 (1.04)	0.0421*** (6.66)	0.0960** (2.57)	0.1660*** (7.22)
INOV	0.0318*** (6.85)	0.0323*** (2.82)	0.0314*** (2.76)	0.0214 (0.63)	0.0207*** (9.07)	0.0321*** (2.80)	0.00057 (0.10)
URBAN	−0.0207*** (−3.15)	−0.0204 (−1.09)	−0.0222 (−1.17)	−0.205*** (−3.22)	−0.0391*** (−19.73)	−0.0213 (−1.11)	0.0091 (0.86)
FDI	−0.00131 (−0.49)	−0.0003 (−0.05)	0.00206 (0.35)	0.0195 (1.39)	−0.0191*** (−13.26)	−0.0008 (−0.15)	0.0003 (0.11)
INDUST	−0.0049*** (−8.65)	−0.0048** (−2.54)	−0.0052*** (−2.81)	−0.0293*** (−5.19)	0.0064*** (22.38)	−0.0047** (−2.42)	−0.0029*** (−2.66)
TEMP	−0.0282*** (−3.71)	−0.0274*** (−3.41)	−0.0248*** (−3.18)	0.0164 (−0.39)	0.0036*** (3.48)	−0.0275*** (−3.35)	−0.0157*** (−2.94)
RAIN	−0.0465** (−2.45)	−0.0458*** (−2.67)	−0.0513*** (−2.93)	0.250*** (3.18)	0.0835*** (14.84)	−0.0472*** (−2.66)	−0.0383*** (−3.66)
WIND	0.0197 (1.55)	0.0190 (1.53)	0.0189 (1.57)	−0.0126 (−0.21)	0.0327*** (7.53)	0.0192 (1.54)	0.0174** (2.29)
$treat_i * post_t * \text{lccp}$		−0.0154 (−0.55)					
$treat_i * post_t * \text{cet}$			−0.0323 (−1.20)				
Constant	−1.763*** (−4.62)	−1.675** (−2.38)	−1.312* (−1.82)	5.067 (0.79)	−1.516*** (−18.91)	−1.660** (−2.36)	−2.007*** (−3.90)
City effect	YES	YES	YES	YES	YES	YES	YES
Time effect	YES	YES	YES	YES	YES	YES	YES
R^2	0.190	0.190	0.201	0.432	NULL	0.190	0.220
N	285	285	285	285	285	281	285
Observations	4,817	4,845	4,845	4,845	4,560	4,777	3,705

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TABLE 6 Heterogeneous effects.

Variables	(1) East	(2) Mid-west	(3) Southeast	(4) Northwest	(5) High-rank	(6) Low-rank	(7) RB	(8) Non-RB
$treat_i * post_t$	0.00656 (0.58)	0.0445* (1.69)	0.0211* (1.88)	0.0961** (2.13)	−0.0126 (−0.94)	0.0360** (2.20)	0.0177 (0.60)	0.0372** (2.27)
Constant	−1.968*** (−5.54)	−1.544 (−1.35)	−1.691*** (−3.42)	−2.235 (−1.21)	−2.413*** (−6.23)	−1.736** (−2.03)	−1.841 (−1.50)	−1.287 (−1.41)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
City effect	YES	YES	YES	YES	YES	YES	YES	YES
Time effect	YES	YES	YES	YES	YES	YES	YE	YES
R^2	0.341	0.234	0.254	0.349	0.809	0.192	0.227	0.195
N	114	171	219	66	19	266	111	174
Observations	1,938	2,907	3,723	1,122	323	4,522	1,887	2,958

Differences in administrative level

In the context of CCM policy implementation, cities with higher administrative levels are likely to possess greater developmental advantages and accrue more benefits. In this paper, the sample cities are classified into two different categories: high-ranking cities (high-ranking), characterized by their high administrative status (including municipalities, sub-provincial cities and certain provincial capitals); and lower administrative-level cities (low-ranking), defined by their low administrative status. The purpose of this classification is to investigate the impact of administrative level on the environmental consequences of CMM policies. Columns (5) and (6) of Table 6 indicate that, in contrast to low-rank cities, the coefficient of the $treat_i * post_t$ in high-rank cities is not significant. This may be attributed to the fact that the CCM reform in high-rank cities primarily enlarges the urban development scale without substantially improving development quality. The municipal district area of high-rank cities expands and may surpass the optimal urban scale due to the implementation of CCM policy, resulting in chaotic development and diminished energy efficiency, ultimately leading to no substantial enhancement in CEE in high-ranking cities.

Differences in resource endowment

Given that cities have diverse resource backgrounds and endowments, they demonstrate significant variations in energy consumption and industrial composition. These differences indirectly affect the mechanisms through which CCM policies influence urban CEE [56]. Based on the criteria established by the central government of China, this paper categorizes the sample cities into two distinct groups: resource-based (RB) cities and non-resource-based (NRB) cities. It then proceeds to investigate the heterogeneous effects of the CCM reform on CEE. The estimates are consolidated in columns (7) and (8) of Table 6. The coefficients of $treat * post$ exhibit noticeable variations across different groups, suggesting that the influence of CCM reform on CEE demonstrates considerable geographical variety. In contrast to RB cities, the CCM strategy has a more substantial and beneficial effect on CEE for non-resource-based cities (NRB) cities.

Mediation mechanism tests

As a significant measure for governments at all levels to attain the objectives of urban administration and regional development within China's hierarchical administrative framework, the CCM strategy exerts both direct and indirect influences on CEE in modified cities. This section analyzes the potential mechanisms by which the CCM strategy facilitates CEE. This paper investigates the transmission pathways and mediating mechanisms of CEE resulting from CCM policy, informed by previous research and theoretical frameworks outlined in Section 2, with the findings detailed in Table 7.

Columns (1) and (5) clearly demonstrate a considerable decline in the coefficient, suggesting that the implementation of CCM can enhance CEE by modifying urban spatial organization. The findings in Columns (2) and (5) demonstrate that CCM enhances urban polycentricity and, hence, fosters CEE. The results of the mechanism analysis presented in Columns (3) and (5) demonstrate that urban compactness is significantly enhanced as a result of CCM, thereby contributing to an increase in CEE. It is crucial to recognize that the mediating effect of urban land use structure remains unverified, as

TABLE 7 The results of mediating effects.

Variables	(1)	(2)	(3)	(4)	(5)
	CEE	Polycentricity	Compactness	Mixedness	CEE
$treat_i * post_t$	0.0368** (2.48)	0.0209** (2.46)	0.0526*** (2.82)	0.00384 (0.60)	0.0260* (1.93)
Polycentricity					0.347*** (2.81)
Compactness					0.0780* (1.87)
Mixedness					−0.142 (−1.29)
Constant	−1.678** (−2.40)	0.0547 (0.15)	−2.314*** (−3.05)	0.670*** (2.90)	−1.422** (−2.09)
Controls	YES	YES	YES	YES	YES
City effect	YES	YES	YES	YES	YES
Time effect	YES	YES	YES	YES	YES
R^2	0.189	0.102	0.964	0.014	0.209
Observations	4,845	4,845	4,845	4,845	4,845

TABLE 8 The Moran's index of China's urban CEE during 2003 to 2019.

Year	Moran's I	*Z*-value	*p*-value
2003	0.27	7.15	0.00
2004	0.31	7.79	0.00
2005	0.32	8.19	0.00
2006	0.32	8.15	0.00
2007	0.33	8.44	0.00
2008	0.31	8.03	0.00
2009	0.32	8.26	0.00
2010	0.29	7.64	0.00
2011	0.30	7.75	0.00
2012	0.30	7.90	0.00
2013	0.30	7.80	0.00
2014	0.32	8.24	0.00
2015	0.32	8.33	0.00
2016	0.36	9.14	0.00
2017	0.37	9.38	0.00
2018	0.37	9.57	0.00
2019	0.40	10.28	0.00

indicated in Columns (4) and (5). This suggests that it does not significantly contribute to the enhancement of urban CEE. The influence of urban land use structure on CEE is relatively limited, potentially attributable to the multi-factor offset effect, the predominant role of technology and policy, temporal lag effects, and constraints imposed by research methodologies. First, the carbon source and sink effects associated with different land use types may counterbalance one another, thereby diminishing the overall correlation. Second, in the short term, direct measures for emission reduction, such as energy structure optimization and clean technology application, contribute more significantly to efficiency enhancement, overshadowing the long-term impact of land use structure adjustments. Additionally, the effects of land use changes on CEE exhibit spatiotemporal accumulation and regional heterogeneity, which may dilute localized impacts when analyzed comprehensively. Lastly, existing research data or model methods may contain inaccuracies, leading to measurement errors that fail to fully capture the complex nonlinear relationship between urban land use structure and CEE. Thus, the active implementation of the CCM approach, by promoting multi-centrality and urban compactness, can significantly improve the CEE of urban regions.

Further analysis: spatial spillover effect

Spatial autocorrelation test

As previously stated, urban regions are frequently interconnected rather than isolated. Numerous studies indicate that the CEE of urban areas exhibits a significant regional spillover effect, potentially resulting in biases in the aforementioned estimation outcomes due to the neglect of spatial correlations among regions. This research subsequently introduces spatial econometric models to investigate the spatial spillover effects of the CCM policy on CEE.

This study constructs a spatial weight matrix based on the rook proximity rule, as spatial correlation is essential for conducting spatial regression analysis. Additionally, ArcGIS software is employed to calculate the global Moran's I index of CEE from 2003 to 2019. Table 8 shows that the Moran's I indices for CEE are all positive and surpass the 1% significance levels threshold from 2003 to 2019, demonstrating a robust positive correlation in China's CEE and underscoring the necessity of employing spatial econometric models. This research employs the SDM to investigate the spatial effects of CCM policy on CEE. This approach is grounded in the results of several diagnostic tests, including the LM test, robust LM test, LR test, Wald test, and Hausman test.

Spatial spillover effect test

The SDM regression results show that the coefficient of the spatial lag term is positive (0.02) and statistically significant at the 1% level of significance. The findings indicate that the level of CEE exhibits a substantial positive spatial spillover effect; thus, enhancing a city's CEE will consequently elevate the CEE in its surrounding areas. This study investigates the direct and indirect impacts of CCM policy on CEE. Table 9 indicate that the direct impact coefficient of the CCM policy is 0.037 and the indirect impact coefficient is 0.046, both of which demonstrate statistical significance at the 5% level. It indicates that the implementation of the CCM reform not only enhances local

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TABLE 9 The decomposition results of spatial effects for spatial Durbin model.

Variables	(1)	(2)	(3)
	Direct effect	Indirect effect	Total effect
$treat_i * post_t$	0.037*** (0.00)	0.046** (0.03)	0.082*** (0.00)
POP	0.413*** (0.00)	0.246** (0.01)	0.659*** (0.00)
GDP	0.099*** (0.00)	−0.109*** (0.00)	−0.010 (0.77)
INOV	0.032*** (0.00)	−0.010 (0.29)	0.022** (0.03)
URBAN	−0.020*** (0.00)	0.015 (0.23)	−0.005 (0.70)
FDI	−0.001	−0.003	−0.004
	(0.80)	(0.56)	(0.54)
INDUST	−0.005*** (0.00)	0.002** (0.02)	−0.002** (0.03)
TEMP	−0.029*** (0.00)	0.020 (0.17)	−0.008 (0.63)
RAIN	−0.045** (0.01)	0.123*** (0.00)	0.077* (0.06)
WIND	0.018 (0.13)	−0.027 (0.34)	−0.008 (0.80)

CEE but also improves CEE in adjacent areas. The CCM policy facilitates the upgrading of industrial structures, boosts energy efficiency, and promotes the advancement of green innovative technologies in surrounding cities through spatial abatement effects.

Discussion

In China, the state possesses the power to reorganize the administrative division system to facilitate geographic or spatial urban development and assumes a supervisory, managerial, and participatory role during rapid urbanization, contrasting markedly with the roles in advanced nations of North America and Western Europe. This paper investigates the environmental effects of CCM from the perspective of CEE, which constitutes the principal contribution of this research. The results indicate that CCM has beneficial environmental consequences, which is similar to previous studies (Shao et al., 2018).

Urban spatial structure is a crucial indicator of resource allocation. It swiftly adapts to the execution of diverse government policies and significantly influences social and economic benefits, regional coordination, and environmental sustainability. This paper builds an index of urban spatial structure encompassing three dimensions—urban polycentricity, urban compactness, and urban land use—and uses it as a substitute variable for the impact of the CCM on CEE.

This approach diverges from previous studies (Chung and Lam, 2004; Hu, 2018) that analyzed the social and economic advantages of ABA from a fiscal and tax authority standpoint, offering substantial implications for future urban governance and spatial resource distribution. Furthermore, urban carbon emissions in Central and Eastern Europe exhibit significant spatial spillover effects, as they traverse regions without hindrance from administrative boundaries. This paper examines the spatial spillover effect of CCM on urban CEE, drawing on prior research on ABA (Feng et al., 2020; Song et al., 2020), which constitutes a principal contribution of this study.

Nevertheless, this paper has specific shortcomings. The influences of other kinds of ABA strategies on urban spatial structure and carbon efficiency are diverse. We will carry out an in-depth study on whether these strategies possess environmental benefits and what the mechanisms therein are. Furthermore, owing to disparities in administrative division systems, this paper's research focus is confined to China, and its conclusions may markedly diverge from those of industrialized Western nations. Subsequent research should analyze the socioeconomic and environmental effects of the ABA across various nations.

Conclusion

The ABA has evolved into an effective strategy for urban administration and governance in China, garnering the attention of many researchers. Despite several studies indicating that the execution of ABA policy enhances the social economy and spatial configuration of cities, its comprehensive impact on the urban environment remains unexamined. This paper takes the CCM as a case study to explore the mechanism through which it affects CEE and provides strong evidence for the environmental changes driven by government actions, using a panel dataset of 285 cities in China from 2003 to 2019.

This paper presents the primary conclusions as follows: this study applies SBM-DEA to compute the CEE and investigates the impact of CCM policy on CEE through DID model. The baseline regression and robustness tests indicate that the implementation of CCM policy significantly improves urban CEE, and this research findings are both effective and robust. The results of the heterogeneity analysis show that the carbon efficiency improvement effect of CCM is more significant in mid-western, northwestern, low-rank and non-RB cities compared to eastern, southeastern, high-rank and RB cities.

Secondly, this study investigates whether the implementation of CCM will enhance urban spatial organization and thus augment CEE. This analysis investigates the mediating effect of urban spatial structure on climate change through three variables: urban polycentricity, compactness, and land use mixing degree, all of which are correlated with climate change mitigation (CCM) and CEE. The findings suggest that the enhancement of urban spatial structure contributes to the improvement of CEE in cities where the CCM has been implemented. Furthermore, we find that augmenting urban polycentricity and compactness would markedly improve CEE, but modifying land use structure is presently negligible.

Ultimately, we examine the spatial spillover effect employing a spatial econometric model. The spatial autocorrelation test results revealed a significant spatial correlation in CEE, indicating that enhancing a city's CEE will also positively impact the efficiency of neighboring cities. According to the SPDM findings, the execution of the CCM strategy enhances not only the CEE of the cities themselves but also that of adjacent cities.

This paper presents a plausible strategy for sustainable growth in China and other emerging nations, along with substantial evidence for low-carbon urban development. Given that the CCM policy can perpetually enhance urban spatial organization and improve CEE, it is recommended that the government extend the policy's implementation range and proactively showcase the advantageous impact of the modified city. Simultaneously, the government ought to implement CCM to enhance urban spatial configuration through suitable direction. The optimization of industrial and energy structures within urban areas should be expedited through spatial structure adjustments, with the objective of eradicating polluting firms and attaining carbon decoupling in sectors such as transportation and industry. Moreover, policies must be devised to align with the distinctive characteristics of urban areas.

In this regard, mid-western, northwestern, low-ranking, and non-resource-based cities should establish a "multi-center, cluster-oriented" spatial pattern. By leveraging industrial integration demonstration zones, these areas can promote the clustering of industries, construct distributed energy systems, and develop circular economy industrial parks to achieve cascading energy utilization and collaborative waste management. The transportation network can be optimized through creating a low-carbon commuting zone within a 30-kilometer radius that integrates rail transit with new energy buses. Additionally, ecological red line zones should be demarcated, and the carbon sink forest quality enhancement project should be implemented comprehensively. Rooftop photovoltaic potential areas and wind energy-rich belts can simultaneously host integrated scene-storage bases, while digital twin technology can be utilized to establish a carbon emission big data monitoring platform. Through precise alignment of spatial elements, the carbon emission intensity per unit of GDP can be reduced, thereby improving CEE. Whereas eastern, southeastern, high-ranking, and RB cities should systematically optimize their energy structures and reduce the carbon emission intensity of production by advancing industrial digitalization and intelligent upgrading, developing clean energy technologies such as photovoltaic and wind power, constructing zero-carbon industrial parks, enhancing collaborative resource utilization in circular economies, and establishing robust green financial support systems. Simultaneously, they can leverage the large-scale development of emerging technology industries to achieve efficient resource allocation and deep integration of low-carbon technologies, thereby comprehensively improving regional carbon emission efficiency and accelerating the transition to a green and low-carbon economy.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found at: https://www.cnrds.com/Home/Index#/.

Ethics statement

Ethical review and approval were not deemed necessary for the study involving human participants, in accordance with local legislation and institutional requirements. Written informed consent to participate in this study was obtained from the legal guardians or next of kin of the participants.

Author contributions

XF: Formal analysis, Writing – original draft, Writing – review & editing, Funding acquisition, Investigation. SX: Methodology, Writing – original draft.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This research was funded by National Social Science Fund "Investigation into the Performance Assessment and Enhancement Strategies for Post-Disaster Emergency Financial Expenditure grant number 22BZZ094".

Acknowledgments

During the research process, the geographical information data of administrative divisions provided by the Hubei University significantly facilitated our field research. The Institute generously shared its previous research data and materials with us. Furthermore, during the paper-writing phase, the Institute offered valuable suggestions on data processing and revisions to relevant chapters.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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