DIGITAL ECONOMY AGGLOMERATION AND CO_2 MARGINAL ABATEMENT COSTS IN CHINESE CITIES: AN EMPIRICAL TEST BASED ON SPATIAL PANEL MODELING

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Abstract. As a novel growth driver, the digital economy is critical in achieving carbon emission reductions. Based on the Spatial Durbin Model (SBM), this paper measures the marginal abatement cost of CO_2 emissions (MAC) of 274 cities in China from 2011 to 2022. It analyzes the time-series evolution and spatial distribution of the digital economy (DE) and MAC. The SBM is used to test the influence process and underlying mechanisms empirically. The results show that (1) DE and MAC spatio-temporal heterogeneity was significant. Over the 2011-2022 period, MAC and DE show an overall upward trend, with MAC higher in eastern cities than in central and western China, reflecting the higher marginal cost of emission reduction in developed regions. (2) DE and MAC spatial correlation is enhanced. Moran's I index continues to rise, indicating a gradual increase in the degree of spatial agglomeration of DE and MAC. (3) DE has a significant negative impact on the local MAC and a notable adverse spillover effect on MAC in neighboring areas. (4) DE can reduce MAC through two distinct avenues: progress in green technology and industrial structure upgrading. (5) The dampening effect of DE on MAC is more pronounced in non-resource cities and areas characterized by high financial development. This study may serve as a valuable reference for achieving a green and low-carbon transition at a low cost.
Keywords: *digital economy, marginal abatement cost of CO_2 emissions, shadow price, spatial panel model, ecological environmental quality*

Introduction

As global industrialization and economic growth have accelerated, the issue of CO_2 emissions has become increasingly prominent. CO_2 emissions impede human socio-economic development and the attainment of global sustainable development goals. According to data released by the International Energy Agency, China's overall CO_2 emissions, which reached 12.1 billion tons in 2022, represent approximately one-third of the world's total CO2 emissions (https://www.iea.org/reports/CO2-emis-sions-in-2022). Considering its responsibility for reducing CO_2 emissions to address global warming and the environmental impacts of socio-economic progress, China has set a target to peak carbon dioxide emissions by 2030 and achieve carbon neutrality by 2060 (Cheng et al., 2022). With these dual objectives in mind, policies such as direct government regulation, carbon taxes, and carbon trading have been proposed. Regardless of the policies adopted by the Chinese government, an effective emission reduction program must follow the

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principle of equal marginal abatement costs. In other words, the price of the last unit of CO_2 reduction paid by each economic actor must be consistent (Liu and Feng, 2018). This implies that clarifying the MAC of the emission-reducing entity is the key to optimizing emission reduction policy. The MAC not only directly reflects the connection between environmental quality and economic growth but also serves as the basis for differentiated climate policies at the global, national, and local levels.

Meanwhile, DE has grown faster and had a broader impact than ever before. DE has become an essential driving force for enhancing new dynamics of economic development and constructing new national competitive advantages to reshape the international competitive landscape (Li et al., 2022). According to data released in the White Paper on the Development of China's Digital Economy, the proportion of DE in the GDP was 41.5% in 2022, with an annual rate of 10.3% (http://m.caict.ac.cn/yjcg/202007/-P0202007033182566 37020). This suggests that DE plays a significant role in China's economic development. DE increases factor supply through digitization, improves factor allocation efficiency using networking, and enhances output effectiveness with the help of intelligence. This process promotes changes in the economy's quality, efficiency, and dynamics and provides a solution path to address the tension between economic growth and environmental protection (Cheng et al., 2023). DE is beginning to reduce CO_2 emissions, but how it affects MAC is still worth studying in depth. Therefore, scientific assessment of DE's impact on MAC not only accelerates DE's development but also can slow down climate deterioration.

In light of the aforementioned research background, this paper employs the non-radial and non-directional SBM to assess the MAC of 274 cities in China from 2011 to 2022. Through the spatial Durbin model, we also investigate the spatial effects and discuss mechanisms of DE's impact on MAC. This study offers four main contributions. Firstly, the study quantifies the MAC at the municipal level in China and then presents the basic facts of China's MAC with a more micro-regional unit. Within Chinese urban clusters, this helps to understand the present state of emission reduction from a cost standpoint. Secondly, from a spatial perspective, this paper tests the trend of DE on MAC with increasing economic geographic distance, further refining the analysis of DE's spatial influence on MAC. This provides a theoretical basis for inter-regional measures to jointly reduce MAC. Thirdly, it empirically tests how DE can enhance the progress of green technology and industrial structure upgrading. Therefore, it can reduce MAC in the region and enrich the existing mechanism research. Fourthly, this paper examines the impact of DE on MAC regarding city resource endowment and city financial level, which enables city managers to select differentiated governance strategies.

Literature review

Measurement of MAC

MAC, representing the decrease in economic output per unit of CO_2 reduction (Cheng et al., 2022), reflects the opportunity cost of CO_2 reduction. Alternatively, MAC can reflect the potential for CO_2 reductions by different entities and the degree of scarcity of CO_2 emission rights for each subject. In the environmental economics literature, distance functions are commonly utilized to obtain the marginal abatement cost or implicit price of pollutants (Zhou et al., 2014). This approach uses a multiple input-output framework in which production processes produce desired and undesired outputs (polluting emissions). The primary methods for estimating shadow prices encompass both parametric and non-

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parametric approaches. The parametric approach is also known as the stochastic frontier analysis (SFA) method. This method requires a predefined specific form of production function, which parameterizes the directional distance function using transcendental logarithmic or quadratic forms to determine the shadow price of CO_2 emissions (Färe et al., 2005). For example, Du and Mao (2015) in China explored the environmental performance, abatement space, and marginal abatement cost of coal-fired power plants using parametric linear programming. Using the parametric method, Wei and Zhang (2020) demonstrated that the estimate of shadow prices varies significantly across different levels of disposability. Zhang et al. (2022) measured the marginal abatement costs of SO_2 and COD using stochastic frontier analysis (SFA) quadratic functions and taking Chinese industrial enterprises as research objects. Non-parametric approaches are described as Data Envelopment Analysis (DEA). This method employs DEA to estimate the production frontier, avoiding pre-specified assumptions about the production function, allowing for inefficient production behavior, and decomposing multifactor productivity (Wu et al., 2019a; Karasu et al., 2020). Many researchers have applied this approach in their studies. Such as Wu et al. (2019b) measured and analyzed MAC for the tertiary industry in each province of China. Wang et al. (2020) estimated MAC for 33 coal-burning power facilities in China. In summary, the functional form selected has a considerable influence on the estimation outcomes of parametric methods. Therefore, measuring marginal abatement costs using non-parametric methods is the most widely employed approach.

Impact of DE on carbon emissions

In the studies examining the factors influencing MAC, more scholars focus on carbon emission reduction policies (Xu et al., 2022), carbon emission intensity and efficiency (Ao et al., 2023; Cheng et al., 2022), energy structure (Peng et al., 2012), industrial structure (Zhong et al., 2023), scientific and technological progress (Rausch and Yonezawa, 2023) and other perspectives for research. The economic effects of DE have been the focus of academic research (Guo et al., 2020). The advent of dual-carbon goals has prompted a growing number of scholars to examine the potential of DE in reducing carbon emissions (Li et al., 2024; Wang et al., 2024). First, the relationship between DE and carbon emissions. Based on the research, it can be divided into three specific categories: facilitative, inhibitory, and non-linear effects. Scholars who support the promotion theory argue that DE is becoming an increasingly primary factor in China's carbon emissions (Yuan et al., 2021). The initial phase of DE can crowd out capital investment in the production sector, reducing carbon efficiency (Zhao et al., 2022). Those who espouse the inhibition theory posit that the impacts of structural improvement, technological advancement, and optimized resource allocation in DE inhibit urban carbon emissions significantly (Ozturk and Ullah, 2022; Li and Wang, 2022). Nevertheless, several researchers believe that the relationship between DE and carbon intensity is best described by a non-linear, inverted U-shaped curve rather than a simple linear association (Cheng et al., 2023). Alternatively, during the initial phases of DE growth, DE failed to reduce carbon emissions, even increasing them. Second, the impact mechanisms and pathways of carbon emission reduction with DE. Existing studies have mainly analyzed them from a technological enhancement and energy utilization efficiency standpoint. The function of DE for technological innovation is manifested in two ways. For one thing, digital technology is a crucial driver of innovation, embracing more efficient and cleaner technological solutions and contributing to the development of low-carbon technologies and renewable energy sources (Liao et al., 2024). Furthermore, an information platform

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was established between enterprises and banks through DE, which reduces the search cost for enterprises and connects their financing, production, and operations, ensuring that enterprises have sufficient funds for green R&D (Li et al., 2024). An energy efficiency pathway is one in which DE improves energy utilization (Tang et al., 2021; Zhu and Lan, 2023). Developing and deploying digital technologies, such as information and communication technology, internet technology, and big data, can significantly advance businesses' digitalization and intelligent upgrades. This contributes to a reduction in resource and energy consumption, which in turn leads to a decrease in carbon emissions. The latest studies on the link between DE and carbon emissions are inconclusive. One potential explanation for this debate is the relatively biased selection of carbon emission indicators and the fragmented nature of the action mechanism.

In other words, there are still three limitations in current studies. First, the research dimensions are primarily at the macro level, focusing on provincial regions and industries, with a limited number of studies concentrating on MAC at the urban scale. Second, most existing studies have measured carbon emissions or intensity to evaluate regional low-carbon progress. This research has investigated the relationship between DE and carbon emissions or intensity. The relationship can only illustrate the reduction of emissions through DE. However, it cannot capture its influence on economic development, even though it is more difficult to systematically reflect the impact on the level of regional low-carbon development. Third, most studies use fixed-effects models to identify the effects of DE and carbon emissions but overlook the spatial dimensions of carbon emissions. Furthermore, some research focused on the spatial evolution characteristics of carbon emissions. These studies only considered geographic factors while ignoring economic factors when setting the spatial weighting matrix.

Hypothesis development

Impact of DE on MAC

DE may have an impact on MAC through endowment effects, governance effects, and social effects. Firstly, the endowment effect. DE has data, technology, and networks as its core endowment. The high circulation of data elements helps to break down information barriers (Huang et al., 2022). Digital technologies can optimize production processes and improve resource and energy efficiency (Li et al., 2024a). Digital platforms, on the other hand, promote information sharing and synergy in the industry chain (Dong et al., 2024). These may directly reduce the difficulty and cost of achieving emission reduction targets. Secondly, the governance effect. DE has enhanced the government's capacity to monitor and govern carbon emissions. Digital technology enables the government to monitor energy consumption and emissions of pollution in real time, thereby strengthening corporate carbon regulation and optimizing the efficiency of carbon governance (Medaglia et al., 2024). This may reduce overall abatement costs. Thirdly, the social effect. DE enhances residents' environmental awareness and monitoring capabilities. Residents monitor companies' low-carbon production behaviors through media coverage and online communication (Zhao et al., 2022). They aggregate and disclose corporations' environmental information to raise public awareness of environmental issues. These initiatives can exert social pressure on polluting firms to increase investment in green technology innovations (Liao, 2018; Du et al., 2019), significantly reduce pollution emissions, and thus may curb MAC. Although the abatement potential of DE is widely discussed, its specific pathways and combined effects on MAC at the city level require

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empirical testing in greater depth. In particular, the mechanisms by which DE acts on MAC through the aforementioned triple effects of endowment, governance and society are also examined. This helps to understand the economic logic of digital technology-enabled emission reduction more comprehensively and provides new perspectives for formulating more precise low-carbon development policies. This is a significant contribution to existing research on the environmental impacts of DE and a practical guide on how cities can leverage digital transformation to lower the cost of achieving “dual carbon” targets. In summary, this paper posits Hypothesis 1:

H1: DE can significantly reduce urban MAC.

DE, green technological progress, and MAC

Existing literature explores the potential positive impact of DE on green technology innovation and green total factor productivity (Ge et al., 2024; Xu et al., 2024). This suggests that green technological advances (green technological innovation and green total factor productivity) may be an important way for DE to influence city-side MAC. The specific mechanisms are analyzed as follows: Firstly, digital technology improves resource allocation (Sun et al., 2024). Digital technologies help enterprises search for and match green technology information and innovation elements more efficiently, reducing related transaction costs and time. This stimulates the incentives of enterprises to conduct green R&D and transform their results (Li and Zhou, 2024), generating a “technology dividend” that may, in turn, reduce the marginal cost of achieving emission reduction targets. Secondly, DE has helped green finance and sustainable investing to grow. The sharing, platform, and inclusive features of DE may alleviate information asymmetry, making it easier for companies to obtain financing for their green projects (Ma, 2023). At the same time, digitized green financial instruments can help guide the precise flow of funds to environmental industries and low-carbon projects (Chang et al., 2023). This promotes the innovation and commercial application of green technologies, as well as the spread of clean energy, and accelerates the process of emission reduction. Empowered by green technologies, enterprises (especially energy-intensive enterprises) may improve energy use efficiency through energy substitution, end-of-pipe treatment technologies, and intelligent transformation. This reduces efficiency losses and reliance on conventional energy sources (Miao et al., 2024), potentially lowering their abatement costs. This is despite concerns about the impact of DE on green technologies and their potential benefits in terms of emission reductions. However, there is still a need for more systematic empirical tests on how DE can reduce urban MAC by integrating the key mediating pathways of influencing green technology innovation and green total factor productivity. An in-depth exploration of this mediating mechanism can help clarify the economic logic underlying DE-enabled reductions in emissions. This will provide a more operational basis for policymakers to utilize digital technologies to enhance the overall efficiency of emission reduction. In summary, we posit Hypothesis 2:

H2: DE generates green technologies to carry out and thus reduce urban MAC through green technology innovation and the green total factor productivity.

DE, industrial structure upgrading, and MAC

DE promotes the upgrading of industrial structure through the development of digital industries and the digital transformation of traditional industries, thereby may facilitating the low-carbon transition and sustainable growth of urban areas (Zuo et al., 2024). First,

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DE empowers the transformation of traditional industries. DE helps resources break through time and space constraints, promoting the penetration of digital technology in traditional industries (Bai et al., 2023). This promotes the transformation of labor-intensive and energy-intensive industries into technology-intensive and environmentally friendly ones, as well as the digital upgrading of traditional industries. Second, DE fosters the emergence of new digital industries. The development of DE is likely to accelerate the convergence of digital technologies with high-carbon-emitting industries, giving rise to new products, business forms, and models (Zhang and Zhao, 2024). The innovation and industrialization of digital technologies help form technology-intensive and environmentally friendly digital industry clusters, promoting the evolution of industrial structure towards low-carbon and high-level development. Third, there is potential for emission reductions through upgrading the industrial structure. An advanced industrial structure is considered a potentially effective path to reduce MAC. On the one hand, service-led structures are generally less energy-intensive. On the other hand, the upgrading process itself may be more conducive to the development and application of low-carbon technologies to reduce emissions at source. An in-depth investigation of the mechanism by which DE affects MAC through industrial structure upgrading can enrich the theoretical understanding of the transmission channels of DE environmental effects. This can better inform the development of city policies that rely on digital technologies to promote the green and low-carbon transformation of industries. This highlights the value of this study's focus on the mediating aspect of industrial structural upgrading. By and large, this research puts forward the following hypothesis:

H3: DE reduces MAC by promoting industrial structural upgrading.

Materials and methods

Variable measurement

Estimating the MAC

This paper uses a non-parametric approach to measure urban MAC in China. The methodology's core lies in constructing a dyadic model of the DEA approach to assess the shadow price of CO_2. Specifically, when a linear programming model is subject to constraints, it aims to maximize the production of a set of products through an overall objective function that maximizes overall benefit. At this point, an optimal solution exists for the dual variables in its dual model, which represents the shadow price of the corresponding resource (Li and Wang, 2022). The DEA is a non-parametric efficiency analysis method that compares the efficiency of Decision-Making Units (DMUs) by constructing an optimal production frontier based on input-output indicators using linear programming. The model is non-radial compared to the traditional DEA model; it allows for disproportionate changes in inputs and outputs, better reflecting the complexities of actual production environments. Therefore, we employ the non-radial, non-orientated SBM for measuring the MAC.

The paper estimates the MAC using the non-radial and non-oriented SBM. There are three main steps.

Firstly, assume that x, y, and b are factor inputs, desired outputs, and undesired outputs. Nonparametric linear programming for the sample containing K decision-making units (DMU_o) is designed in *Equation 1*.

$$s.t.\begin{cases}(\theta^*) = min\dfrac{1-\frac{1}{M}\sum_{m=1}^{M}\frac{s_{mo}^{x}}{x_{mo}}}{1+\frac{1}{Z+J}(\sum_{z=1}^{Z}\frac{s_{zo}^{y}}{y_{zo}}+\sum_{j=1}^{J}\frac{s_{jo}^{b}}{b_{jo}})} \\ x_{mo} \geq \sum_{k=1}^{K}\lambda_k\, x_{mk} + s_{mo}^{x} \\ y_{zo} \leq \sum_{k=1}^{K}\lambda_k\, y_{zk} - s_{zo}^{y} \\ b_{jo} = \sum_{k=1}^{K}\lambda_k\, y_{jk} - s_{jo}^{b} \\ s_{mo}^{x} \geq 0, s_{zo}^{x} \geq 0, s_{jo}^{x} \geq 0, \lambda_k \geq 0\end{cases} \quad \text{(Eq.1)}$$

M, Z, and J represent the numbers of x, y, and b, respectively. θ^* is the emissions efficiency of DMU_o, and $0 < \theta \leq 1$. so is the relaxation variable. s_{mo}^{x}, s_{jo}^{b} indicate the potential reductions in input and undesirable output, and s_{zo}^{y} indicates the potential increase in desirable output. λ_k is the intensity variable, and $\lambda_k \geq 0$ indicates a constant return to scale production technology.

Secondly, the paper applies the Charnes-Cooper transformation (Wang and Feng, 2015) on *Equation 1* to obtain *Equation 2*.

$$\max u^{y}\, y_o - u^{x}x_o - u^{b}b_0 \quad \text{(Eq.2)}$$

$$s.t.\begin{cases}\sum_{z=1}^{Z}u_z^{y}\, y_{zo} - \sum_{m=1}^{M}u_m^{x}\, x_{mo} - \sum_{j=1}^{J}u_j^{b}\, b_{jo} \leq 0 \\ u^{x} \geq \frac{1}{M}(1/x_o) \\ u^{y} \geq \frac{1-u^{x}x_o-u^{b}b_o+u^{y}y_o}{Z+J}(1/y_o) \\ u^{b} \geq \frac{1-u^{x}x_o-u^{b}b_o+u^{y}y_o}{Z+J}(1/b_o)\end{cases}$$

u_m^{x}, u_z^{y} and u_j^{b} are the virtual prices of x, y, and b, respectively.

Finally, the shadow price of desired output is assumed to be equal to the market price (Cheng et al., 2022), p^{y} is equal to 1. The shadow price is shown in *Equation 3*.

$$p^{b} = p^{y} \times \frac{u^{b}}{u^{y}} \quad \text{(Eq.3)}$$

Empirical specification

To explore the spatial effect of DE on MAC through various types of tests, this paper applies the Spatial Durbin Model (SDM) (see *Eq. 4*):

$$LMAC_{it} = \alpha_0 + \beta\sum_{j=1}^{n}W_{ij}\, LMAC_{it} + \alpha_1 LDE_{it} + \alpha_2 Control_{it} + \varphi_1\sum_{j=1}^{n}W_{ij}\, LDE_{it} + \varphi_2\sum_{j=1}^{n}W_{ij}\, Control_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad \text{(Eq.4)}$$

where MAC_{it} represents the marginal abatement cost of urban CO_2. DE indicates the degree of digital economic development. $Control_{it}$ represents control variables. represents the constant term. β represents the spatial regression coefficient for the dependent variable; W_{ij} represents the spatial weight matrix. To consider the effects of both geographic and economic factors, the geographic distance spatial matrix and the economic distance spatial matrix were constructed by nesting the matrices. $\alpha_1$represents

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the coefficient for the explanatory variables. φ_1 represents the spatial regression coefficient for the explanatory variable; μ_i refers to spatial trait effect; δ_t is the time trait effect; ε_{it} is the time trait effect.

Variables selection

(1) Explained variable. LMAC: The paper first selects input and output indicators (see *Table 1* for specific measurements), then estimates the marginal abatement cost of CO_2 emissions (MAC) using the SBM, and finally takes the logarithm of the estimated value to obtain LMAC.

(2) Explanatory variable. LDE: In this study, we construct a comprehensive evaluation index system for the digital economy (DE) based on the research of Zou and Deng (2022). This system was developed from internet development and digital financial inclusion. To assess the level of internet development at the city level, four key indicators were identified: The number of internet broadband access subscribers per 100 population, the share of employees in computer services and software, the per capita telecommunications service volume, and the number of cell phone subscribers per 100 population. To assess the development of digital finance, the "Peking University Digital Finance Index" as compiled by Guo et al. (2020) was utilized. In this study, principal component analysis was used to numerically standardize and effectively downscale the five selected key indicators, thereby obtaining the DE index. Furthermore, this study uses the natural break method to categorize the levels of DE development. The zoning methodology employed in related studies (Xu et al., 2015) was also used in this investigation. The DE obtained from the measurement was categorized into four areas: Pioneer, Advancing, Catching up, and Lagging, based on the natural break method

(3) Mechanism variables. The intermediary factors in this study include progress in green technology and industrial structure upgrading (IS). Green technological innovation is expressed in terms of green technological innovation capacity (GI) and green total factor productivity (Gtp). GI is measured by the logarithm of the number of patents granted for green inventions, and the GML index measures Gtp based on the SBM directional distance function. The advanced industrial structure is a measure of IS, and this paper adopts the ratio of the output value of the tertiary industry to that of the secondary sector to measure it.

(4) Control variables. They specifically include foreign trade (TR), The level of human capital (HR), Financial development (Fin), The level of economic development (LGDP), Road passenger traffic (LPas), Expenditure on science (LSE).

Data sources

In this paper, Chinese cities are selected as a sample. The study period spans from 2011 to 2022. MAC data are primarily sourced from the China Energy Statistical Yearbook, the EPS database, and the National Statistical Yearbook. The digital economy data are primarily sourced from the China Urban Statistical Yearbook, the China Urban Digital Economy Development Report, and the China Digital Economy Development White Paper. Data on mechanism variables were mainly obtained from the EPS database and the State Intellectual Property Office of China. For severely missing data, this paper removes them. For the small portion of missing data, interpolation is used in this paper to supplement the data. Finally, this paper compiles relevant data for 274 cities in China, resulting in a total of 3288 observations. Descriptive statistics for eight indicators are

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presented in *Table 2*. These statistics include the mean, standard deviation, minimum, and maximum values, providing an overview of the central tendency and variability of these indicators.

Table 1. *Variable definitions*

Variables	Name	Description
Explained variable	*LMAC*	Labor x: The number of employees per unit (unit: ten thousand people) Energy x: Annual energy consumption (unit: Million tonnes of standard coal)[a] Capital x: Fixed asset capital stock (unit: one hundred million yuan), it is calculated by perpetual inventory method y: Regional GDP (unit: one hundred million yuan) b: Carbon emissions (unit: one hundred thousand tons) are calculated based on the consumption of electricity, natural gas, liquefied petroleum gas, and thermal energy
Explanatory variable	*LDE*	Level of development of the digital economy according to principal component analysis
Mechanism variables	*GI*	The logarithm of the total number of green patent authorizations
	Gtp	The SBM is used to measure Gtp. Notably, the input and output variables are measured using the same indicators as those used to calculate MAC, except for non-expected outputs, which are measured using industrial sulfur dioxide, wastewater, and soot emissions
	IS	Tertiary sector output/secondary sector output
Control variables	*TR*	Total trade exports and imports/regional GDP
	HR	Number of students enrolled in general higher education/population of the region
	Fin	Balance of deposits and loans of financial institutions/regional GDP
	LGDP	The logarithm of GDP per capita
	LPas	The logarithm of road passenger traffic
	LSE	The logarithm of regional science expenditures

[a]The heat emissions are equivalent to one unit of energy per standard coal, and in this paper, energy consumption is converted to standard coal with reference to (Wu et al., 2023)

Table 2. *Summary statistics*

Variable	N	Mean	SD	Max	Min
LMAC	3288	-1.395	1.218	1.560	-4.345
DE	3288	0.443	0.801	3.957	-1.656
TR	3288	0.195	0.324	3.078	0.0001
HR	3288	0.030	0.026	0.210	0.000
Fin	3288	6.330	1.120	8.232	2.675
LGDP	3288	10.749	0.554	13.043	8.753
LPas	3288	8.203	1.105	12.466	4.123
LSE	3288	10.490	1.430	15.629	6.524

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Characterization of the facts

Characterization of temporal evolution

Characterization of the temporal evolution of DE

To more graphically and intuitively demonstrate the distribution location and morphology of urban DE in China, the extension characteristics and the degree of polarization. This paper presents a three-dimensional kernel density estimation plot. *Figure 1* illustrates DE's dynamic distribution and evolutionary trend from 2011 to 2022 Examining *Figure 1* reveals several noteworthy characteristics of China's urban DE development. First, the center of the distribution curve for urban DE in China demonstrates a general rightward shift and an overall increase. This indicates an overall enhancement in the advancement of DE across Chinese urban areas. Second, the distribution of DE curves in Chinese cities exhibits a right-tailed phenomenon. This suggests the existence of cities with very high levels of DE that stay ahead of the curve at the high-level stage. Third, the distribution of DE curves in Chinese cities exhibits multiple peaks, with the highest peak occurring at a value of 0.8. This suggests a multi-polarized character to DE within China, with most of the sample group concentrated around 0.8. Fourth, the peak of the kernel density curve for DE is high and dense between 2011 and 2013, indicating that DE is characterized by a high degree of concentration. Subsequently, the peak of the kernel density curve for DE exhibited a gradual decline and widening. This indicates that the rate of development between cities is no longer uniform but gradually widening the distance, resulting in the formation of a so-called "digital divide" and a multilayered structure. The "Matthew effect" is becoming increasingly evident in urban DE advancement, aligning with the conclusions drawn by Yu et al. (2024). As a result, China's urban DE exhibits two distinct characteristics: a continuous increase in the overall level of advancement and a widening gap between cities.

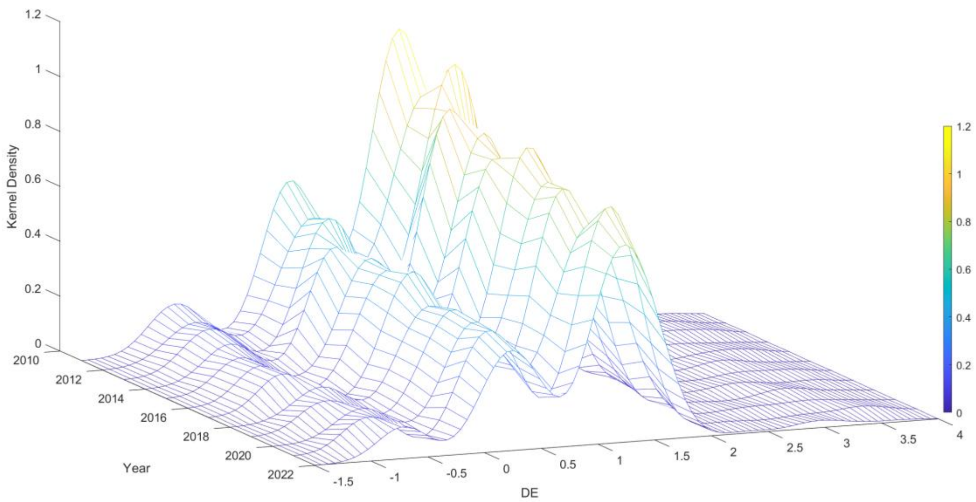

Figure 1. *The kernel density curve of the DE*

Characterization of the temporal evolution of MAC

Figure 2 shows the MAC trends in the national, eastern, central, and western areas from 2011 to 2022. MAC increased from 2011 to 2022, with the average value rising from 0.339

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to 0.674 thousand yuan/ton. Previously, much of the literature estimated the MAC in China. There are differences in the distance functions, estimation methods, and variables used by these studies to characterize undesired outputs. Due to differences in the distance function, the estimation method, and the variables representing undesired outputs. The estimated value of MAC in China ranges from 0.0021 thousand yuan/ton (Lee and Zhang, 2012) to 50.4 thousand yuan/ton (Cheng et al., 2022). The MAC measured in this paper falls within this range, indicating that the measurements have some credibility. Based on the standard regional division methodology published by the National Bureau of Statistics of China, this paper analyses the city into eastern, central, and western regions. The trends in MAC in the eastern, central, and western areas are generally in line with the national trend, with all areas experiencing slow increases. Compared to the central and western regions, the MAC in the eastern cities is higher, increasing from 0.428 thousand yuan/ton to 0.811 thousand yuan/ton. The eastern region has a more developed economy, advanced production technologies, and greater energy utilization than other areas. The price they must pay to reduce the MAC further is also higher. Notably, the MAC in the central area is lower than in the western part, which matches the findings of Wu et al. (2020), who assessed the MAC across Chinese provinces. The industrial layout in the western region is skewed towards resource-dependent and energy-intensive industries, and the efficiency of green innovation is relatively low. This implies a higher cost in the West for the same emission reduction target. MAC may also be related to the region's technological innovation capacity and industrial structure.

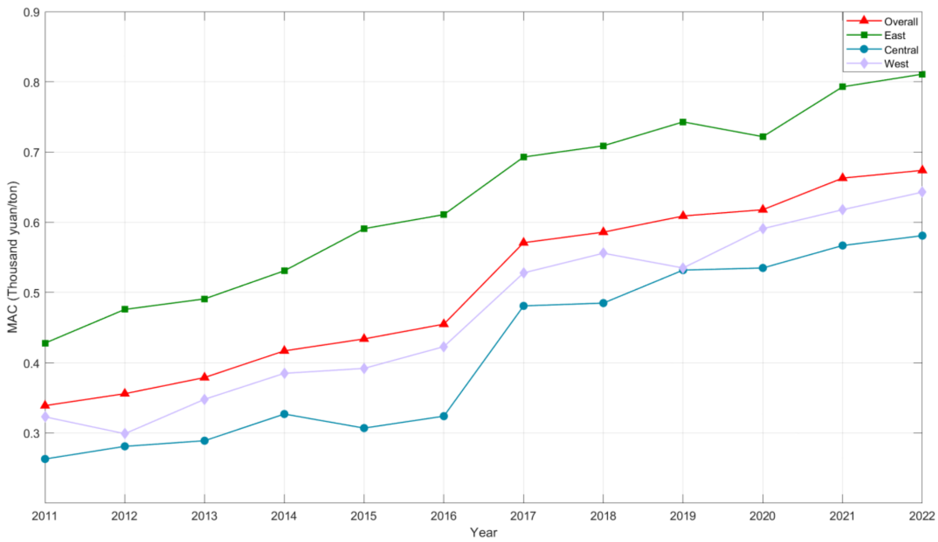

Figure 2. *Trends in the MAC of Chinese cities*

To visualize the dynamic distribution of MAC, this paper plots the kernel density estimation in three dimensions. According to *Figure 3*, first, the MAC kernel density curves of Chinese cities show an overall rightward shifting trend, indicating that the MAC of most Chinese cities is continuously increasing. This aligns with the findings of Du and Mao (2015). Second, the MAC kernel density curves show prominent and dense peak tips in the early stage, reflecting the highly concentrated nature of MAC. Starting in 2017, the peak height of China's urban MAC kernel density curve has decreased significantly, and the width gradually widened. This suggests that the MAC gap between cities is widening.

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Third, there is a significant right-trailing phenomenon in the distribution curve of China's urban MAC, indicating that some cities with MAC are significantly higher than those of other cities in the same region. Fourth, the distribution of the MAC kernel density curves shows a clear single peak with an insignificant secondary central peak. This suggests that there is no multi-polar differentiation of urban MAC in China.

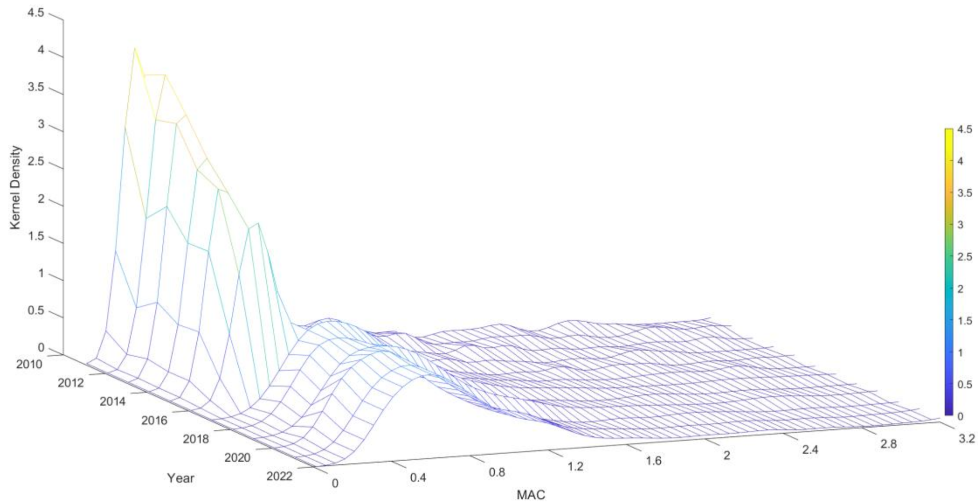

Figure 3. *The kernel density curve of the MAC*

Characteristics of the spatial distribution

Characteristics of the spatial distribution of DE

To further reveal the spatial characteristics of DE in Chinese prefecture-level cities and visualize them using ArcGIS 10.7 software, *Figure 4* was obtained by plotting. Over time, the landscape of DE has undergone significant changes. There has been a shift from a scattered distribution with several pilot zones to a clustered development with city clusters, and the DE dynamics of many cities have increased significantly. Notably, the DE lagging areas experienced a significant catch-up between 2011 and 2016, closing the gap with districts with higher levels of DE. The DE catching-up area also emphasizes DE development, gradually transforming into an advancing area. Due to the limitations of factors such as factor endowments, location, and development fundamentals, there are significant regional differences in economic progress. Eventually, a DE development pattern will be formed with the Beijing-Tianjin-Hebei, Chengdu-Chongqing city cluster, Yangtze River Delta, and other city clusters serving as its core. In particular, the Yangtze River Delta region is particularly pronounced. Specifically, in 2011, the level of DE was generally low in most cities due to the lack of prerequisites for DE, including insufficient digital infrastructure, limited innovation capacity, and a shortage of professional personnel. Inter-regional disparities in DE are more pronounced, and spatial imbalances in DE are particularly pronounced. By 2021, DE in China's urban agglomerations had made significant progress. The core cities played a leading role and radiated to the surrounding areas, forming a new pattern of cluster development. This change is due to two aspects: First, digital technologies in core cities have a spillover effect, promoting the synergistic development of neighboring cities. Second, the rational flow of digital resources from the core city to the periphery has reshaped the spatial pattern of regional development.

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Characteristics of the spatial distribution of MAC

This paper categorizes MAC into five classes using the natural break method in ArcGIS 10.7 software. They are less than 0.188 thousand yuan/ton, 0.189-0.575 thousand yuan/ton, 0.576-1.243 thousand yuan/ton, 1.244-2.239 thousand yuan/ton, and more than 2.240 thousand yuan/ton, respectively, which are plotted to obtain *Figure 5*. From 2011-2022, the MAC shows an upward trend in most cities, and the growth trend gradually shifts to the east. The binding carbon emission reduction targets in 2011-2015 are likely responsible for this trend. Subsequently, several low-carbon policies have been implemented that could significantly reduce carbon emissions per unit of GDP. The sharp reduction in CO_2 emission intensity signals a gradual weakening of the economies of scale of carbon emission reductions. When easily achievable emission reductions are effectively adopted, achieving further carbon emission reductions becomes increasingly costly, and the MAC continues to rise (Du and Mao, 2015). In terms of spatial distribution, urban MACs exhibit greater spatial heterogeneity. MAC is higher in the eastern coastal areas and more economically developed urban centers in central China, with notable concentrations in cities such as Suzhou, Shenzhen, Guangzhou, and Wuhan. This indicates a more developed economy where the cost of reducing a unit of CO_2 is higher. The pricing strategy for the future carbon trading scheme is likely to affect the spatial distribution of the industry. The eastern region is likely to gradually relocate high-carbon secondary industries with high carbon emissions to the central and western parts of the country. In addition, some resource cities have relatively high MACs, such as Baotou and Ordos. This may be because heating systems in northern cities depend strongly on coal. The primary sources of heating heat come from cogeneration and various types of coal-fired production. In summary, China's overall MAC has been on an upward trend since 2011, and its spatial distribution has also undergone a significant trajectory of change.

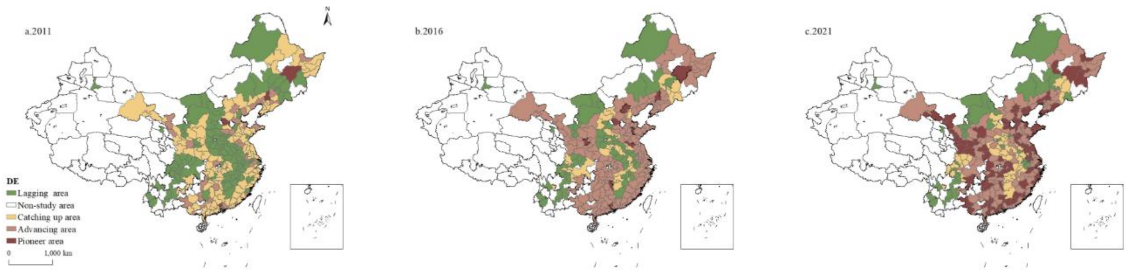

***Figure 4.** DE spatial distributions in the Chinese cities for 2011, 2016, and 2021*

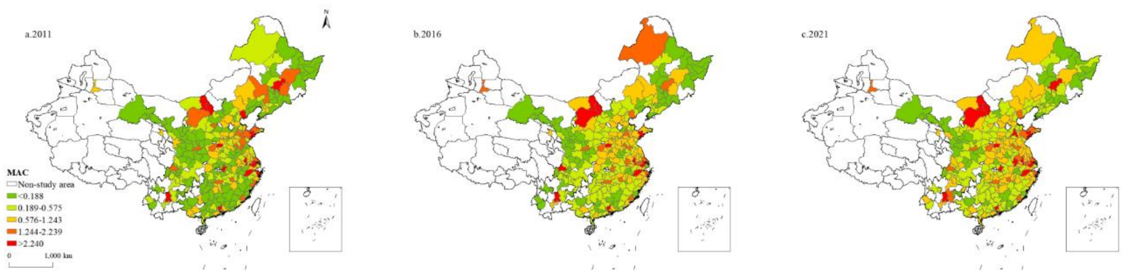

***Figure 5.** MAC spatial distributions in the Chinese cities for 2011, 2016, and 2021*

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Spatial correlation analysis

This study employs the global Moran's I index to analyze the spatial auto-correlation of DE and MAC for 274 cities in China (see *Table 3*). The Moran's I index for DE and MAC passes the 1% significance level under the economic-geographical nested matrix. Numerically, Moran's I indexes are all positive, indicating that DE and MAC have significant spatial clustering characteristics. The global Moran's I index for both shows a general upward trend over the study period, indicating a gradual increase in their spatial clustering.

Table 3. *Results of spatial auto-correlation test*

Year	DE		MAC	
	I	Z(I)	I	Z(I)
2011	0.076***	15.117	0.042***	8.647
2012	0.078***	15.413	0.044***	8.885
2013	0.082***	16.223	0.044***	9.053
2014	0.085***	16.772	0.047***	9.493
2015	0.072***	14.324	0.053***	10.583
2016	0.084***	16.525	0.053***	10.650
2017	0.079***	15.639	0.058***	11.693
2018	0.081***	16.038	0.059***	11.630
2019	0.082***	16.140	0.064***	12.839
2020	0.077***	15.214	0.062***	12.455
2021	0.082***	16.091	0.064***	12.686
2022	0.076***	15.973	0.065***	13.573

***, * and * indicate 1%, 5% and 10% significance levels, respectively. Test: Z(I) > 1.96 indicates at 5% level of significance and Z(I) > 2.58 indicates at 1% level of significance

Empirical results and analysis

Baseline regression results

We first performed the LM, LR, and Hausman tests (*Table 4*). Test findings indicate that SDM with double fixed effects is the most suitable choice for analyzing the spatial effect of DE on MAC (*Table 5*). Model (1) controls only for city and year-fixed factors. The results show that DE coefficient is significantly negative. Model (2) includes all control variables, and the coefficient on DE remains significantly negative. This indicates that DE markedly reduces MAC in the region, supporting Hypothesis 1.

The level of human capital (*HR*) and economic development (*LGDP*) have a significant positive impact on MAC. Possible reasons Human resources are an essential element in driving economic development. Regions with higher levels of human resources also show stronger economic growth. As the economic development of the region increases, so does the economic cost of reducing a unit of non-consensual production. Similarly, the regression coefficients for road passenger traffic (*LPas*) are significantly positive. An increase in road passenger transport is accompanied by a corresponding rise in tailpipe emissions from vehicles, thereby contributing to increased air pollution. The regression coefficient for expenditure on science (LSE) is significantly positive. Regional expenditure on science is often used for research and development of

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low-carbon technologies. These technologies have long research and development cycles, high investments, and uncertainty about technological breakthroughs. In the early stages of technology development, high R&D costs and substantial resources are required, and significant emission reductions are typically not visible in the short term. In contrast, the level of financial development (*Fin*) has a significant negative impact on MAC. Regions with advanced financial systems have more developed markets and improved access to finance. This makes it easier for firms to obtain low-cost finance for investing in low-carbon technologies and abatement projects, thereby helping to reduce marginal abatement costs.

Table 4. *Model selection test*

Test methods	Test statistic results	P
LM-Lag	3.979	0.0460
Robust LM-Lag	23.504	0.0000
LM-Error	13.490	0.0000
Robust LM-Error	33.015	0.0000
LR-SDM-SEM	33.220	0.0000
LR-SDM-SAR	32.791	0.0000
Hausman	33.360	0.0000

Table 5. *Estimation results and model recognition verification of spatial panel Durbin model*

Variables	(1) x	(2) W × x	(3) x	(4) W × x
DE	-0.1072*** (-4.2599)	-0.4627*** (-6.1985)	-0.3110*** (-14.0361)	-0.1550** (-2.1762)
TR			-0.0348 (-0.5872)	1.1139*** (5.0001)
HR			0.0007*** (8.9010)	0.0001 (0.1829)
Fin			-0.1165*** (-3.4259)	-0.3028** (-2.3433)
LGDP			0.0000*** (6.9142)	-0.0000 (-0.9132)
LPas			0.0755*** (3.8523)	-0.0304 (-0.4795)
LSE			0.3263*** (18.7830)	-0.0774 (-1.3101)
rho	0.5300*** (18.7333)		0.1033*** (2.7901)	
sigma2_e	1.1901*** (40.0557)		0.8018*** (40.5015)	
City	Yes		Yes	
Year	Yes		Yes	
Observations	3288		3288	
R^2	0.048		0.331	

Values in parentheses are the corresponding t-statistics. ***, ** and * indicate significant at the 1%, 5% and 10% levels, respectively (the same below)

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This paper examines the spatial spillover effect of DE on MAC, as shown in *Table 6*. Column (1) shows that each 1-unit increase in DE reduces the MAC by 0.3181 units and the neighborhood's MAC by 0.2102 units. This suggests that the environmental improvement effects generated by DE have some spillover effect on neighboring areas. The development of DE as a determinant of spatial economic layout breaks the established constraints of geography, information, and time costs, enabling the sharing of technology and knowledge spillovers. This means that DE can reduce the costs of inter-temporal dissemination, promote coordinated development between neighboring regions, and reduce urban MAC.

Table 6. *Direct effects, indirect effects, and total effect results*

Variables	(1) LR_Direct	(2) LR_Indirect	(3) LR_Total
DE	-0.3171*** (-13.2871)	-0.2105*** (-2.5101)	-0.5273*** (-6.0839)
TR	-0.0165 (-0.2550)	1.2523*** (4.4705)	1.2560*** (4.4985)
HR	0.0008*** (8.8104)	0.0002 (0.5117)	0.0008** (2.1624)
Fin	-0.1213*** (-3.7015)	-0.3954*** (-2.6765)	-0.5162*** (-3.5642)
LGDP	0.0000*** (6.9435)	-0.0000 (-0.4483)	0.0000** (2.2462)
LPas	0.0745*** (3.6540)	-0.0565 (-0.7604)	0.0165 (0.2057)
LSE	0.3173*** (17.1838)	-0.0545 (-0.7850)	0.2627*** (3.4664)

Robustness tests

To ensure the scientific validity of the results, this study examines four key aspects. First, to address potential endogeneity concerns, this paper employs a lagged one-period DE instead of DE. Second, to address the influence of outliers on the estimates, this study implements a 1% shrinkage on the DE. Third, to test the impact of the time sample factor, this paper excludes the first and last time samples. Fourth, directly administered municipalities differ significantly from other regions in terms of economic strength and technological progress. In this paper, municipalities are eliminated and then brought back. *Table 7* shows that the negative relationship between DE and MAC does not change, confirming the robustness of Hypothesis 1.

Mechanism testing

Examining the role of green technological advances

From columns (1) and (3) in *Table 8*, the estimated coefficients of DE are significantly positive, indicating that DE can enhance green technological innovation (GI) and green total factor productivity (Gtp). The results in columns (2) and (4) show that the estimated

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coefficients of GI and Gtp are significantly negative. This suggests that increases in GI and Gtp significantly affect the suppression of MAC. It is also demonstrated that green technology progress mediates DE and MAC, and the above results confirm Hypothesis 2. The progress of green technology is evident in two key areas: First, the cost of energy use has fallen due to improved green innovation capacity. Second, the reduction in energy dependency per unit of GDP and the increase in sustainability achieved through enhanced green production efficiency. Meanwhile, DE has stimulated the emergence of many new technologies and applications that drive the progress and evolution of emission reduction technologies (Mohd Suki et al., 2022). Technological advances in emission reduction reduce MAC by increasing energy efficiency, and improving the energy mix, reducing energy consumption and waste, and promoting the widespread adoption of clean energy (Khatami et al., 2023). As a result, the transmission path is "DE - (promoting) emission reduction technologies - (suppressing) MAC." This suggests that the goal of carbon reduction can be achieved through high-quality development without compromising economic growth.

Table 7. *Results of robustness test*

Variables	**(1)** ***LMAC***	**(2)** ***LMAC***	**(3)** ***LMAC***	**(4)** ***LMAC***
L.DE	-0.3056*** (-12.9573)			
DE		-0.3170*** (-13.6561)	-0.3322*** (-14.1608)	-0.3248*** (-14.7746)
W × DE	-0.1463* (-1.9435)	-0.1569** (-2.1212)	-0.2198*** (-2.9179)	-0.1099 (-1.5553)
Controls	Yes	Yes	Yes	Yes
W × controls	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
rho	0.1061*** (2.7375)	0.1035*** (2.6732)	0.1027** (2.5126)	0.1128*** (3.0095)
sigma2_e	0.8085*** (38.7743)	0.8040*** (38.7862)	0.7486*** (36.9716)	0.7620*** (40.2017)
Observations	2989	3288	2594	2966
R^2	0.328	0.337	0.369	0.383

Examining the role of industrial structural upgrading

Column 5 of the table demonstrates that DE has a considerable influence on enhancing the industrial structure (*IS*). The coefficient of IS in column (6) is found to be significantly negative. This suggests that DE has the potential to facilitate industrial structural upgrading, which in turn could help to mitigate MAC. The aforementioned results substantiate the assertion that industrial structure upgrading serves as a mediator of DE to inhibit MAC, thereby corroborating Hypothesis 3. DE has gradually become a "lubricant" between industries. DE optimizes the industrial structure through technological penetration and industrial integration, thereby exerting a significant

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influence on the city's green transformation. Specifically, first, the differential penetration of digital technology into different industries facilitates the modernization and enhancement of the industrial structure, which in turn serves to reduce the MAC. The rapid advancement of digital technology has precipitated beneficial transformations across many industrial sectors. The advent of new-generation technologies, such as artificial intelligence, may give rise to biased substitution effects between labor and capital. Such technologies can potentially drive industrial transformation and modernization by facilitating the movement of production factors across different sectors. China's industrial structure is gradually transitioning from a capital-intensive to a technology-intensive model. This transformation has facilitated a fundamental shift in the industrial model, transitioning from a high-carbon-emitting and extensive model to a low-carbon-emitting and intensive one. Second, the thorough integration of DE into traditional sectors has promoted the upgrading and overall optimization of the industrial structure. This helps to reduce the MAC. DE is characterized by informatization, networking, and digitization. It can facilitate the traditional manufacturing industry in realizing resource allocation more efficiently and reshaping its production mode and profit model (Kofi Adom et al., 2012). This enables companies to enhance the intelligence and decarbonization of their production and R&D processes.

Table 8. *Mediation effect test results*

Variables	(1) *GI*	(2) *LMAC*	(3) *Gtp*	(4) *LMAC*	(5) *IS*	(6) *LMAC*
DE	0.1354***	-0.2927***	0.1123***	-0.2591***	0.1281***	-0.2727***
	(8.0865)	(-13.0615)	(60.4112)	(-8.0521)	(11.1498)	(-12.2276)
GI		-0.0001***				
		(-4.4635)				
Gtp				-0.4540**		-0.3024***
IS				(-2.1828)		(-9.0971)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
rho	0.1543***	0.0912**	-0.1345***	0.1045***	0.1067***	0.1119***
	(4.0327)	(2.4301)	(-3.5368)	(2.8229)	(2.7786)	(3.0177)
sigma2_e	0.4825***	0.7956***	0.0056***	0.8004***	0.2157***	0.7819***
	(40.4502)	(40.6056)	(40.5115)	(40.5011)	(40.5047)	(40.4987)
Observations	3288	3288	3288	3288	3288	3288
R^2	0.764	0.339	0.504	0.330	0.286	0.320

Heterogeneity test

Urban resource endowment

In the traditional theory of economic growth, abundant natural resources are regarded as a fundamental prerequisite for the industrialization process, offering a robust assurance of high-quality economic development. This study aims to determine whether the impact of DE on MAC varies in urban areas with disparate resource endowments. This study employs the classification standards delineated in the National Sustainable Development

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Plan for Resource-based Cities (2013-2020), issued by the State Council (https://www.gov.cn/zhengce/content/2013-12/02/content_4549.htm). The sample is divided into two groups: resource-based cities and non-resource-based. The results of the analysis of differences in resource endowments are presented in *Table 9*. DE significantly negatively affected MAC in non-resource cities, whereas no such impact was observed in resource cities. The reason may be that the economies of resource-based cities are highly dependent on resource industries. This dependency deprives them of the impetus for technological penetration and industrial integration, resulting in a “resource curse” for DE-enabled low-carbon transformation (Abraham, 2021). Conversely, the digital infrastructure and platforms of non-resource cities are comparatively well-developed. These cities are committed to developing green innovation technologies and accelerating their integration with low-carbon transition technologies to curb MAC (Li et al., 2024b).

Table 9. *Results of the test for spatial heterogeneity of resource endowments*

Variables	**(1)** **Resource** ***LMAC***	**(2)** **Non-Resource** ***LMAC***
DE	-0.0308 (-1.0013)	-0.4338*** (-11.4556)
W × DE	0.7432*** (8.6395)	-0.3593*** (-3.2848)
Controls	Yes	Yes
W × controls	Yes	Yes
City	Yes	Yes
Year	Yes	Yes
rho	0.4646*** (12.8892)	0.1295** (2.4355)
sigma2_e	1.1303*** (31.3565)	0.7766*** (25.1935)
Observations	1272	2016
R^2	0.064	0.336

Level of urban finance

This section analyzes the varying impact of DE on MAC across cities with differing financial conditions. This paper uses year-end loan balances as a proxy for the city’s financial development level, grouping and testing the data by median. In this instance, cities exhibiting financial development that exceeds the median are classified as high-financial-development cities. In contrast, those demonstrating a level of financial development below the median are classified as low-financial-development cities. The results of the urban finance testing are presented in *Table 10*. The results demonstrate that DE has a significantly negative impact on MAC in cities with high financial development. In contrast, DE does not affect on MAC in cities with low financial development. This may be because the digital economy has an impact on resource allocation. Higher financial development areas with diversified financial institutions, well-developed financial markets, and active capital flows. The above advantages can address the

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financing needs of traditional industries, integrate and reorganize factor resources, match market supply and requirements on a broader scale, and develop digital technologies and low-carbon products. This suggests that strong financial support provides good security and a permissive environment for the effective use of IT in urban governance, and DE helps to curb MAC.

Table 10. *Results of regressions on spatial heterogeneity of urban financial levels*

Variables	**(1)** **High financial development areas** ***LMAC***	**(2)** **Low financial development areas** ***LMAC***
DE	-0.1143*** (-3.4184)	0.0803 (1.4353)
W × DE	-0.4303*** (-3.5925)	-0.0332 (-0.2243)
Controls	Yes	Yes
W × controls	Yes	Yes
City	Yes	Yes
Year	Yes	Yes
rho	0.0925*	-0.0043 (-0.0951)
sigma2_e	0.9584*** (28.7385)	0.2043*** (28.5653)
Observations	1656	1632
R^2	0.386	0.023

Discussion

The study’s results have significant implications for the development of the digital economy (DE) in China, promoting low-carbon emission reduction. The empirical results show that DE significantly reduces the marginal abatement cost (MAC) of carbon in Chinese cities and their neighboring cities. This finding aligns with previous studies that have emphasized the role of DE in driving reductions in low carbon emissions (Ozturk and Ullah, 2022; Li and Wang, 2022). At the same time, it confirms the effectiveness of policy frameworks such as China’s 13th and 14th Five-Year Plans in promoting integrated sustainable development.

The findings of this study differ from those in the previous literature in three ways. Firstly, existing studies mainly focus on the effect of DE on carbon emissions or carbon emission intensity (Ao et al., 2023; Cheng et al., 2022), while this study focuses on MAC. MAC is a crucial but less-studied indicator for optimizing climate policy. By measuring MAC at the city level, this study mitigates potential biases in macro-level analyses. Secondly, unlike studies that ignore spatial correlations or use simple geographic weights (He et al., 2018; Cui et al., 2022), this study employs a nested economic geospatial matrix to reveal the spillover effects of DE in economic networks rigorously. Thirdly, this study verifies the mediating effect of green technology progress and industrial structure upgrading, which solves the problem of previous fragmented explanations.

The research in this paper also has some limitations. Firstly, similar to most existing studies, the examination of the marginal abatement cost of carbon in this paper is limited

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to an economic output perspective. In reality, however, the costs arising from carbon emissions are not only reflected in a decline in economic output but may also include other costs. From this perspective, this paper's estimate of the marginal abatement cost of carbon is incomplete. Secondly, the scale of the study could be more microscopic. This paper examines the mechanism of DE's influence on MAC based on the perspective of Chinese cities. Future research could delve into the more microcosmic county level to explore the relationship between the two. Finally, the data time frame could be extended. Due to data availability constraints, this paper utilizes data from 2011 to 2022 only. Future studies could use the updated data to validate and expand our findings.

Research conclusions and suggestions

Conclusions

This paper uses shadow price to calculate MAC and analyze DE and MAC's time series evolution and spatial distribution. The influence mechanism of DE and MAC is empirically tested by applying the spatial Durbin model. The empirical results demonstrate that:

DE and MAC spatio-temporal heterogeneity was significant. Over the 2011-2022 period, MAC and DE show an overall upward trend, with MAC higher in eastern cities than in central and western China, reflecting the higher marginal cost of emission reduction in developed regions.

DE and MAC spatial correlation is enhanced. Moran's I index continues to rise, indicating a gradual increase in the degree of spatial agglomeration of DE and MAC.

(3) DE significantly reduces local city MAC and has a substantially negative impact on neighboring MAC.

(4) DE contributes to a decrease in MAC by promoting the progress of green technology and upgrading industrial structures.

(5) The dampening effect of DE on MAC can be heterogeneous depending on factor endowments and the level of financial development. The suppression of MAC by DE is more significant in non-resource cities and high-financial-development regions than in resource cities and low-financial-development regions.

Suggestions

Based on the preceding findings, this study offers relevant recommendations in three areas: First, regions should vigorously develop DE to enhance urban digitization. Regions should invest in expanding digital infrastructure, including the development of artificial intelligence, 5G networks, and base stations. These measures will help expand the application scenarios of digital technology in the "dual carbon" focus areas and promote the in-depth integration of digital technology with traditional industries, thereby reducing the MAC. Second, the relevant departments need to prioritize green technological innovation and maximize the benefits derived from upgrading the industrial structure. On the one hand, the relevant departments should increase R&D funding and personnel investment. These measures aim to encourage enterprises to research and develop low-carbon energy technologies, thereby catalyzing the emission reduction effect of their technological innovations and enhancing their technological support capabilities. On the other hand, relevant departments should use innovative technologies to transform traditional industries into intelligent, networked, and low-carbon sectors. This will

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improve conventional industries' resource allocation and productivity and break their dependence on traditional paths. Thereby reducing the MAC. Third, the relevant departments should adopt differentiated governance measures according to the different characteristics of each region. Each region should combine its resource endowment and advantages to adjust the pace of DE development. This promotes the cross-regional mobility of production factors in the digital economy. Relevant departments should utilize DE's spillover and radiation effects to achieve coordinated promotion of carbon emission reduction among regions.

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Conflict of interests. The authors declare no competing interests.

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