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ORIGINAL ARTICLE

Carbon abatement costs and digital revolution: An empirical analysis of manufacturing industry

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Abstract This study examines China's carbon abatement costs and the role of digital technology, using provincial panel data from 2000 to 2021. By distinguishing between clean and non-clean energy inputs, we find that the estimated carbon abatement cost significantly exceeds prevailing market trading prices and follows a U-shaped temporal pattern—declining initially and then rising steadily. Our analysis shows that digital technology positively influences carbon abatement costs, primarily through improvements in energy efficiency. This effect varies regionally, with the strongest impacts observed in Central China—an unexpected finding given the conventional emphasis on coastal regions. These insights have important policy implications: (1) carbon pricing mechanisms should be reformed to more accurately reflect the true social cost of emissions; (2) the adoption of clean energy must be accelerated to reduce disparities in abatement costs; and (3) targeted digital investments, particularly in inland provinces, can enhance the effectiveness of emissions reduction strategies. By integrating energy-source differentiation with the dynamics of digital transformation, this study offers a more refined framework for evaluating carbon abatement costs and highlights the need for regionally tailored policies to achieve China's 2060 carbon neutrality goal.

Keywords Carbon abatement cost · Clean energy · Digital technology · Energy policy

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Introduction

The rapid rise in global carbon dioxide emissions has accelerated climate change, with economic activities worldwide contributing significantly to this crisis. As the world's largest developing country and leading carbon emitter, China faces the dual challenge of Maintaining economic growth while reducing emissions. In response, China has pledged to peak carbon emissions by 2030 and achieve carbon neutrality by 2060 (Stern & Xie, 2023). This commitment marks a strategic shift from a GDP-centered growth model to a high-quality development approach that emphasizes efficiency, sustainability, and environmental responsibility.

A key pillar of China's low-carbon transition is the national carbon emission trading system (ETS), which began as a pilot program in eight regions in 2011 and was scaled up nationwide in 2021. By 2023, the ETS had facilitated the cumulative trade of 442 million tons of carbon allowances, valued at approximately 3.5 billion USD, with prices ranging between 7 and 12 USD per ton. The enactment of the Interim Regulations on Carbon Emission Trading Management in 2024 further invigorated the Market, increasing annual trading volume to 189 million tons (valued at 2.6 billion USD) and driving allowance prices up by 22.75%, reaching 14 USD per ton (Ministry of Ecology and Environment, 2024).

While existing studies often rely on carbon market prices to inform mitigation strategies, a growing body of evidence suggests that these prices consistently underestimate the true social costs of carbon emissions (Martin et al., 2016; Boussemart et al., 2017). This discrepancy arises from two key limitations in current research. First, the common practice of aggregating energy inputs fails to account for critical distinctions between clean and non-clean energy sources in calculating carbon abatement costs (CAC) (Acemoglu et al., 2012; Ellabban et al., 2014; Pang et al., 2015; Murshed et al., 2021; Cui et al., 2022; Ali et al., 2023). Second, although digital technologies are widely acknowledged as catalysts for industrial decarbonization (Attaran, 2023; Brynjolfsson & McElheran, 2016), their specific mechanisms of influence on CAC remain insufficiently understood, particularly within the context of China's regional diversity.

To address these research gaps, this study makes three key contributions. First, it develops a novel by-production (BP) model that disaggregates clean (hydropower, nuclear, wind, solar) and non-clean (coal, oil) energy inputs. This model builds on the frameworks of Murty et al. (2012) and Shen et al. (2021a, 2021b), incorporating material balance constraints tailored to China's unique energy mix. Second, using provincial panel data from 2000 to 2021, the study quantitatively examines the dual effects of digitalization—both direct impacts through industrial robot adoption and indirect effects via improvements in energy efficiency. Third, the analysis uncovers a U-shaped temporal trend and significant regional disparities in carbon abatement costs, with Central China showing the strongest digitalization-driven impact. These finding challenges conventional assumptions about the technological dominance of Eastern regions (Ao et al., 2023; Zhou et al., 2018a, 2018b).

Our findings carry direct policy implications for China's dual carbon goals, revealing that market prices systematically underestimate carbon abatement costs. Moreover, the pronounced regional heterogeneity underscores the need for region-specific digital infrastructure investments to support effective emission reduction strategies (Au & Henderson, 2006).

Literature review

Estimation of carbon abatement cost

Carbon abatement cost (CAC) is a widely used metric to quantify the expense associated with reducing carbon dioxide emissions (Liu et al., 2015a, 2015b). It represents the cost of the intended output sacrificed to achieve a reduction in pollutant emissions, specifically carbon dioxide (Zhou et al., 2014). The concept of CAC measures the cost of lowering carbon emissions by one unit through a reduction in economic activity (intended output), holding all other factors constant (Nordhaus, 2017).

The CAC metric offers a straightforward and easily understandable way to assess the cost of reducing emissions and the potential for emission reduction across different economic units (Zhou et al., 2015). Furthermore, it is a critical concept in both the financial and ecological sectors, as it facilitates the assessment of the equilibrium between economic development and environmental pollution (Silva & Magalhães, 2023).

Methods for estimating carbon abatement cost

Precise assessment of the CAC is crucial for effectively navigating the carbon emissions exchange market. The two most common ways to determine CAC at the moment are parametric and non-parametric methods. Parametric methods for estimating production costs require a certain shape for the production function and parameterization of the directional distance function. However, these methods are inherently subjective, and the selection of parameters can substantially influence the accuracy of carbon abatement cost (CAC) estimates (Färe et al., 2007). Moreover, parametric approaches often lack flexibility in accounting for input–output slack variables, which limit their ability to capture inefficiencies and redundancies in the production process (Cecchini et al., 2018). In contrast, non-parametric methods do not depend on pre-specified functional forms, offering greater flexibility and potentially more precise representations of input–output relationships and production inefficiencies (Charnes et al., 1978; Thanassoulis et al., 2016). This adaptability can make non-parametric approaches better suited for capturing the true nature of CAC and guiding more informed decision-making in carbon emissions trading.

On the contrary, defining the production function in advance is unnecessary when using the non-parametric method. It utilizes the correlation between the output distance function and the revenue function, predominantly employing linear programming techniques to compute the environmental production frontier function (Zhou et al., 2018a, 2018b). Unlike parametric methods, nonparametric methods impose fewer assumptions, offer greater flexibility, and can effectively incorporate essential economic axioms, making them well-suited for shadow pricing analysis. Consequently, the nonparametric Data Envelopment Analysis (DEA) method has become the mainstream approach for studying carbon abatement cost (Cheng et al., 2019). The DEA method is employed to assess the comparative effectiveness of decision-making units (DMUs) that have many inputs and outputs, by utilizing corresponding production frontier (Sexton, 1986). Within this framework, the BP technique is a specialized environmental production method based on DEA that adheres to the principle of material balance (Baležentis et al., 2021). It effectively addresses the issue of costly disposability assumptions, providing a scientifically grounded approach to regulating carbon emission reductions in China (Zhao, 2017).

Given the inherent subjectivity and lack of flexibility in parametric methods, non-parametric approaches, particularly DEA and its derivatives such as the BP techniques, have emerged as the predominant trend in current research. These methods are favored due to their less restrictive assumptions, high flexibility, and strong alignment with economic axioms. Their application has not only illuminated the spatial and temporal heterogeneity of Carbon abatement cost but also provided a deeper analysis of the regional differences in carbon abatement costs. This offers a robust empirical foundation for policymakers. Shen et al. (2021a) used the BP model to calculate the cost of reducing carbon emissions. Their method guarantees accurate estimates of the costs associated with reducing pollution by properly connecting the underlying sub-technologies used in production. This approach demonstrates how non-parametric methodologies can provide useful insights into comprehending and tackling regional inequalities in attempts to reduce carbon emissions.

The role of energy sources in carbon abatement cost

Distinguishing between clean and dirty energy is crucial for accurately measuring carbon abatement cost and enhancing environmental efficiency (Cui et al., 2022). Clean energy, such as hydroelectric and wind energy, does not produce pollutants or greenhouse gases and poses no harm to ecosystems, making it supportive of green growth. In contrast, dirty energy sources, like coal and oil, emit significant amounts of greenhouse gases and other harmful pollutants, leading to environmental degradation and hindering green growth. Utilising clean energy helps decrease environmental burdens and enhance environmental efficiency by enabling the production of equivalent or better economic value with the same input, while also achieving ecological efficiency objectives (Anser et al., 2020). Conversely, reliance on dirty energy increases environmental burdens, diminishes environmental efficiency, and results in higher pollution emissions for the same level of output, thereby lowering the economic value per unit of environmental load. Research by Cui et al. (2022) and others highlights the importance of differentiating between clean and non-clean energy sources when measuring efficiency. Their findings suggest that countries like France, Iceland, and the United States may have achieved optimal carbon emissions and green development due to the adoption of cleaner and more efficient production technologies. This underscores the growing global trend toward promoting and adopting clean energy, propelled by the rising demand for safeguarding the environment and achieving sustainable progress.

Nevertheless, the current energy landscape in China, together with its infrastructure limitations and the scarcity of clean energy resources, presents significant challenges in establishing a widespread substitution of traditional energy sources with new forms of energy. Further investigation and exploration are needed to determine the potential for emission reduction in China through adjustments to its energy structure. Song et al. (2016) asserted that the consumption of clean energy, particularly hydropower, could successfully lower the strain on thermal power generation and decrease carbon emissions. Hydropower, which has significantly lower prices compared to thermal power, contributes to reducing energy consumption expenses and immediately decreases the additional cost of carbon emissions. Although there are potential advantages, the prevalence of coal in China's energy combination as well as the difficulty in obtaining full data on clean energy have led to limited research that effectively differentiates between clean and non-clean energy sources when evaluating the cost of lowering carbon emissions. Given the paucity of literature in this area, further in-depth studies are required to determine how different energy sources impact CAC, particularly in light of China's unique energy and economic circumstances.

The relationship between digital technology and carbon emissions

Digital technology plays a critical role in determining carbon abatement costs (CAC) (Acemoglu et al., 2012; Wang et al., 2024). Its advanced data analytics capabilities enable precise monitoring and optimal allocation of production resources, thereby significantly reducing resource waste (Boubaker et al., 2025; Nižetić et al., 2019).

Especially after the outbreak of Covid-19, industrial robots have been more widely applied (Mahmood et al., 2024a, 2024b). Reduced CAC is a result of digital technology's ability to reallocate resources to low-carbon production processes that are both efficient and effective. This enhancement in resource allocation efficiency is a key mechanism through which digital technology influences CAC. Moreover, digital technology drives the intelligent transformation of production models (Zhou et al., 2018a, 2018b). The incorporation of advanced technologies like smart manufacturing and the industrial internet in production processes results in enhanced accuracy and efficiency, reducing the need for human involvement and minimizing energy wastage (Hozdić, 2015). This transformation directly lowers the carbon emission intensity of production activities, which, in turn, affects the CAC. As digital technologies become more widespread, the negative correlation between production efficiency and carbon emissions is expected to strengthen, further contributing to the reduction of CAC (Liu et al., 2024). In addition, digital technologies play a crucial role in advancing and implementing environmentally friendly and low-carbon innovations (Ren et al., 2022; Zhang et al., 2022). These advancements not only contribute to more sustainable production practices but also help to create an environment where lower carbon emissions are achievable at reduced costs. Consequently, digital technology is instrumental in fostering a more sustainable, low-carbon economy, directly impacting the Carbon abatement cost by making carbon-efficient production more attainable.

Moreover, digital platforms enable enterprises to rapidly access global green technology information and market trends, accelerating technological innovation and the transformation of results (Yang et al., 2024). Digital technology enables the advancement of green finance and carbon trading markets by easing the financing and trading of projects aimed at reducing carbon emissions (Feng et al., 2022). By improving the CAC's accuracy and lowering the cost of carbon emission reduction, these green innovation efforts give policymakers more data on which to base their decisions. Within the context of China's economic development, the relationship between digital technology and carbon emissions is complex.

In summary, the existing literature has made substantial strides in advancing our understanding of carbon abatement costs, the interplay between digital technologies and carbon emissions, and the distinctions between clean and non-clean energy sources. Nevertheless, several critical gaps persist. First, the majority of studies aggregate energy inputs into a single category, failing to account for the significant differences between clean and non-clean energy sources. Second, there is a lack of systematic research examining the influence of digital technologies on CAC and the underlying mechanisms driving this relationship. Addressing these gaps, this study contributes to the literature by differentiating between clean and non-clean energy sources to provide a more precise estimation of CAC. Furthermore, it empirically investigates the direct impact of digital technologies on CAC and explores the mechanisms through which this impact occurs. Additionally, the study examines regional heterogeneity in CAC, offering policymakers valuable insights for designing targeted and effective carbon reduction strategies.

Methodology

Technology for environmental production

In order to calculate the cost of reducing undesirable outputs, we begin by defining the environmental production technology for Chinese provinces. The by-production approach by Murty et al. (2012) assumes costly disposability for undesirable outputs while specifying two sub-technologies for environmental production technology. The inputs are further categorized based on whether they contribute to the generation of undesirable outputs or not. This implies that costs related to the disposal of the undesirable outputs can be appraised. Also, the materials balance concept is taken into consideration. BP technology does not impose weak disposability on either intended or undesirable outputs. Instead, it characterizes the production relationship through the intersection of sub-technologies for intended output production and undesirable output production.

Under such a production relationship, the intended output production sub-technology, T_1, transforms clean and polluting inputs into intended outputs. In contrast, the undesirable output production sub-technology, T_2, transforms polluting inputs into undesirable outputs. Input and output disposability, closedness, and convexity are some of the basic criteria that constrain both sub-technologies. The BP technology is the result of the merging of these two sub-technologies.

Murty and Russell (2012) introduced the output-oriented Färe-Grosskopf-Lovell (FGL) index as a computational foundation for BP technology. Although FGL index provides a computational framework for BP technology, it overlooks the connections between sub-technologies. Since the model allows free disposability and imposes costly disposability, it can only ensure a reduction in undesirable outputs without decreasing intended outputs by reducing polluting inputs. Therefore, the abatement cost estimated by the traditional by-production (BP) model may be biased (Baležentis et al., 2021). To address this, Baležentis et al. (2021) enhanced the BP model by explicitly incorporating the relationship between pollutant generation and the technological linkages involved. The dual formulation of this improved BP model can be expressed as follows:

$$
\begin{aligned}
D\left(x, y, z; 0, g_y, g_z\right) = & \min_{\pi_y, \pi_x^b, \pi_x^c, \omega_x^c, \omega_z, v_1, v} \Big(\sum_{b=1}^{B} \pi_x^b, \pi_e^b, + \sum_{c=1}^{C} \pi_x^c, \pi_e^c, \\
& - \sum_{a=1}^{A} \pi_x^a, \pi_e^a, -v_1 + \sum_{d=1}^{D} \omega_z^d, z_e^d, -v_2 \Big) \\
s.t. & \sum_{a=1}^{A} \pi_x^a, \pi_e^a, - \sum_{b=1}^{B} \pi_y^b, \pi_e^b - \left(\sum_{c=1}^{C} \pi_x^c, \pi_e^c + \sum_{c=1}^{C} \omega_x^c, x_e^c \right) + v_1 \le 0, \; e = 1, \ldots, E \\
& \sum_{c=1}^{C} \omega_x^c, x_e^c - \sum_{d=1}^{D} \omega_z^d, x_e^d - v_2 \le 0, \; e = 1, \ldots, E \\
& \pi_y^a, g_e^a \ge 0.5/A, \; a = 1, \ldots, M \\
& \pi_z^d, g_z^d \ge 0.5/D, \; d = 1, \ldots, D \\
& \pi_y^a \ge 0, \; a = 1, \ldots, A \\
& \pi_x^b \ge 0, \; b = 1, \ldots, B \\
& \pi_x^c \ge 0, \; c = 1, \ldots, C \\
& \omega_z^d \ge 0, \; d = 1, \ldots, D
\end{aligned}
\tag{1}
$$

$(0, g_y, g_z)$ represents adjusted non-zero directional vector in the intended output and undesirable output, while keeping the input level constant; K refers to the number of decision-making units; $\pi_x^b, \pi_x^c, \pi_y^a$ are the abatement cost of clean inputs, polluting inputs, and intended outputs, modeled by the intended output production sub-technology; ω_x^c and ω_z^d are the abatement cost of polluted inputs and undesirable outputs, respectively, modeled by the undesirable output production sub-technology; v_1 and v_2 are the dual variables of the intended output production sub-technology and the undesirable output production sub-technology, respectively. Variable returns to scale act as a constraint on them. Although abatement cost derived from the two sub-technologies may differ, the constraint in Eq. (2) accounts for the dual role of undesirable inputs: one in generating the intended output (marginal contribution π_x^c) and the other in producing pollution (marginal contribution ω_x^c). As a result, the abatement cost of polluting inputs, ω_x^c, is consistent across the sub-technologies. This article considers carbon dioxide as the undesirable result and regards value-added for the secondary industry as the intended output.

Estimation of carbon abatement cost

The abatement cost of undesirable output can be expressed as quotient of multiplier related to undesirable output ($\omega_z^{CO_2}$) and the multiplier related with the intended output $\left(\pi_y^{\text{Second}GDP}\right)$. This study quantifies the economic benefit lost in secondary industry when a single unit of carbon dioxide released is reduced as the abatement cost:

$$CAC = \frac{\omega_z^{CO_2}}{\pi_y^{\text{Second}GDP}} \tag{2}$$

Prior research on estimating the cost of carbon abatement has shown a lack of distinction between various forms of energy usage. It is widely recognized that the utilization of polluting energy resources, such as fossil fuels and coal, leads to elevated levels of carbon emission levels, whereas clean energy sources have negligible carbon emissions. Thus, while considering the production of intended and undesirable outputs, it is important to treat energy inputs as separate entities. This study utilizes an improved BP technique to estimate carbon abatement cost, specifically by categorizing provincial energy consumption into dirty and clean energy. In the intended output production sub-technology, all types of energy are included, while in the undesirable output production sub-technology, only dirty energy is considered. The objective of this approach is to offer a more precise assessment of carbon emissions. Equations (2) and the carbon abatement cost (2) are estimated by DEA method.

Theoretical analysis: mechanisms linking industrial robot imports to carbon abatement costs

The rapid adoption of digital technologies, particularly industrial robots, has transformed global production systems, offering new opportunities to address environmental challenges such as carbon emissions. Industrial robots, as a cornerstone of advanced manufacturing, not only enhance productivity but also have the potential to significantly influence carbon abatement strategies. Understanding the mechanisms through which industrial robot imports affect the cost of carbon emission reductions requires a multidisciplinary perspective, integrating insights from environmental economics, technological innovation, and industrial transformation. This section explores the theoretical pathways by which industrial robots contribute to lowering CAC, emphasizing their role in improving production efficiency, enabling energy substitution, achieving economies of scale, fostering knowledge spillovers, and driving structural transformation in the economy.

First, industrial robots, as a key facet of digital technology, enhance production efficiency by automating labor-intensive tasks and optimizing resource utilization (Gao et al., 2022). According to endogenous growth theory (Romer, 1990), technological progress driven by automation fosters more efficient production processes, thereby reducing energy consumption and waste. These efficiency gains lower the marginal cost of production, which consequently decreases the cost of carbon abatement. By substituting traditional, energy-intensive manufacturing methods with precision-driven robotic systems, industrial robots help reduce carbon intensity per unit of output.

Second, the adoption of industrial robots often coincides with the integration of cleaner and more energy-efficient technologies (Ma et al., 2024). As highlighted by the environmental Kuznets curve hypothesis, technological progress can decouple economic growth from environmental degradation. Industrial robots enable the substitution of fossil fuel-based energy with electricity, which can be sourced from renewable energy (Lin & Xu, 2024). This shift reduces greenhouse gas emissions and lowers the overall cost of achieving carbon reduction targets.

Third, the deployment of industrial robots facilitates large-scale production, which can lead to economies of scale in carbon abatement (Arents & Greitans, 2022). As production scales up, the fixed costs of implementing carbon reduction technologies (e.g., carbon capture and storage) are spread over a larger output, reducing the average cost per unit of emission reduction. This scale effect is particularly relevant in industries with high carbon footprints, such as manufacturing and heavy industry.

Fourth, the importation of industrial robots often brings advanced technologies and best practices from developed countries, fostering knowledge diffusion and technological spillovers (Keller, 2004). These spillovers can enhance local firms' capabilities to adopt low-carbon technologies and improve their environmental performance. As a result, the overall cost of carbon abatement decreases at the regional level.

Finally, industrial robots serve as a catalyst for industrial upgrading and structural transformation (He et al., 2022). By automating low-value-added and high-pollution activities, these technologies facilitate a shift toward high-value-added and low-carbon industries. This structural transformation diminishes dependence on carbon-intensive sectors, thereby reducing the overall cost of carbon abatement.

In summary, the adoption of imported industrial robots impacts emission reduction costs through multiple pathways: enhancing production efficiency, improving energy efficiency, promoting green innovation, and driving structural changes in the economy. These mechanisms collectively contribute to a reduction in carbon emissions and lower emission reduction costs, making industrial robots a valuable tool in the transition towards a low-carbon economy.

Modelling the influence of digital technology on the carbon abatement cost

Based on the theoretical considerations above, this study builds a basic model to investigate how digital technology affects the cost of carbon emission reductions:

$$CAC_{it} = \alpha_0 + \alpha_1 Digital_{it} + \sum_{j=1}^{J} \beta_j controls_{itj} + \mu_i + \nu_t + \varepsilon_{it} \quad (3)$$

where CAC_{it} denotes the cost of reducing carbon emissions in province i year t, $Digital_{it}$ denotes the digital technology, and $controls_{itj}$ represents control variables, with j indicating the number of control variables. μ_i and ν_t represent individual effects and random effects. ε_{it} is the random error term. We employ a two-way fixed effects model to estimate Eq. (4).

Variables and data

The performance indicator of this paper is the carbon abatement cost, calculated using the BP approach. The input indicators comprise (i) fixed asset investment in the secondary industry, (ii) the number of employees in the secondary sector, (iii) coal consumption, (iv) crude oil consumption, and (v) clean energy generation (including hydropower, nuclear energy, wind energy and solar power). Fixed assets, employment, and clean energy generation are considered as clean inputs, while coal and crude oil consumption are considered pollutant inputs. The intended output indicator is the incremental value of the secondary industry (measured in billions of yuan, adjusted for inflation), whereas the undesirable output is carbon emissions. The carbon dioxide emissions data are obtained from the China Carbon Accounting Database (CEADs) and are derived from the China province CO2 emission inventory, using the apparent emission accounting approach (Shan et al., 2016, Shan et al., 2018, Shan et al., 2020, Guan et al., 2021). Monetary variables (value-added and investment in fixed assets) are adjusted for inflation using 1997 as the reference year to ensure consistency. The secondary sector encompasses mining, manufacturing, production, electricity, gas, water, and construction. Definitions of key variables for carbon abatement cost estimation are presented in Table 1.

Digitalization technology is measured by the number of industrial robots imported by each province (in 10,000). Following the methods of Acemoglu et al. (2020) and Fan et al. (2021), the adoption of robots in China's manufacturing industry is measured by the number of industrial robots imported, as recorded in the Chinese Customs Database (using the HS8 code). There are eight categories of industrial robots, including handling robots, multifunctional industrial robots, other unlisted industrial robots, automatic handling robots for

Table 1 Definitions of key variables for carbon abatement cost estimation

	Variable	Definition	Obs	Mean	Std. Dev
Input variables	Labor of secondary industry	Employment in the secondary industry in each province (ten thousand people)	660	664	583
	Fixed asset investment in the secondary industry	Fixed asset investment in the secondary industry in each province (100 million yuan, deflated)	660	3087	3627
	Coal consumption	Consumption of coal in each province (ten thousand tons)	660	11689	10119
	crude oil consumption	Consumption of crude oil in each province (ten thousand tons)	660	1519	1938
	Clean energy consumption	The consumption of clean energy, encompassing hydropower, nuclear energy, wind energy, and solar power, is measured for each province in units of hundred million kilowatt-hours	662	381	549
Output variables	Value added of secondary industry	GDP of the secondary industry in each province (100 million yuan, deflated)	663	1278	1064
	Carbon dioxide emissions	Carbon Dioxide Emissions by Province (in million tons)	664	288	273

integrated circuit factories, resistance welding robots, arc welding robots, and laser welding robots. Modern industrial robots are typically equipped with sensors and data collection capabilities, essential for digital Manufacturing and implementing Industry 4.0 (Javaid et al., 2021). Integrating these robots into production processes highlights the adoption of data-driven decision-making and automated processes (Rogers & Zvarikova, 2021). Consequently, industrial robots are a crucial component of advanced manufacturing and automation, representing significant advancements in digital technology. The quantity of imported industrial robots is indicative of a province's degree of embracing advanced technology.

Control variables include the added value of the secondary industry, oil consumption, clean energy generation and labor of secondary industry. The data come from the National Bureau of Statistics in China.

This study focuses on 30 Chinese provinces from 2000 to 2021. Given that data for the indicator of digital technology, namely the import of industrial robots, is available starting from 2012, the examination of the influence of digital technology on carbon abatement cost is Limited to the period from 2012 to 2021. We can divide the 30 provinces into three regions: the eastern, central region, and western. Table 2 presents the descriptive statistics.

Results

Carbon abatement cost estimation

Figure 1 depicts the temporal changes in China's carbon abatement cost from 2000 to 2021. In comparison to the actual carbon trading prices, the estimated

Table 2 Definitions and descriptive statistics of independent variables for empirical model

Variable	Definition (dimension)	Obs	Mean	Std. Dev
Degree of digitization	Number of industrial robots imported by each province (10,000 units)	660	2	6
Value added of secondary industry	GDP of the secondary industry in each province (billion yuan, deflated)	660	1278	1064
Oil consumption	Consumption of petroleum products including kerosene, gasoline, and diesel (ten thousand tons)	660	873	656
Clean energy consumption	Consumption of clean energy in each province (hundred million kilowatt-hours)	660	381	549
Labor of secondary industry	Employment in the secondary industry in each province (ten thousand people)	660	664	583

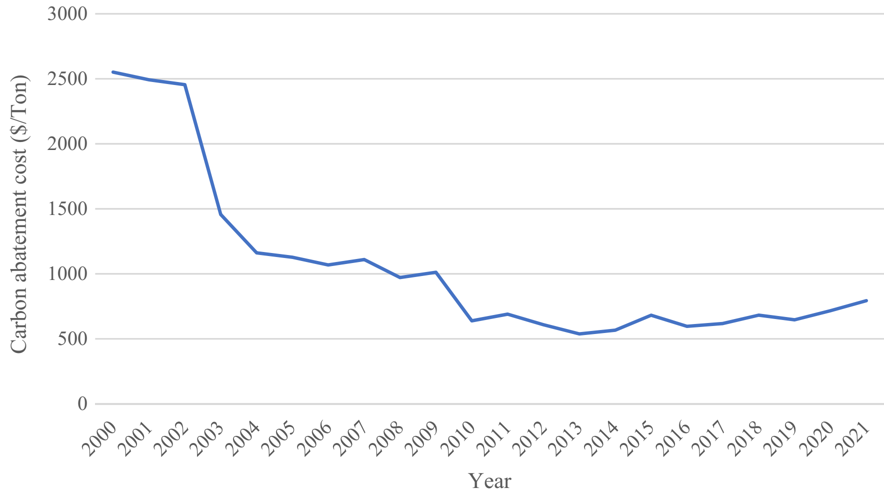

Fig. 1 China's carbon abatement cost (USD/ton)

CAC values are significantly higher, especially in the earlier years. This is because the carbon emission trading price is formed through market transactions of carbon allowances, reflecting the combined influence of market supply and demand, policy environment, and market participants' expectations, among other factors. Currently, China's carbon emission allowance allocation is primarily based on free distribution, which may result in some enterprises receiving more allowances than needed (Liu et al., 2015a, 2015b). This reduces their urgency to purchase additional carbon emission rights, thereby exerting downward pressure on trading prices. In contrast, this study and related research utilize economic modeling to isolate market distortions and quantify the social opportunity cost of carbon reduction (Fang et al., 2019). The results consistently show that the social opportunity cost substantially exceeds current market prices, suggesting that existing carbon pricing mechanisms do not fully capture the true social costs of carbon emissions. This gap points to inefficiencies within the current system and underscores the urgent need for policy reforms that better align carbon market prices with their actual societal costs (Fu et al., 2025).

In this study, it is important to note that higher carbon abatement costs are indicative of better environmental performance. This counterintuitive relationship can be explained by the fact that when a region or enterprise has already optimized its carbon reduction technologies to near-maximum efficiency, the potential for further reductions becomes limited. In such cases, reducing each additional unit of carbon emissions requires a greater sacrifice in terms of GDP, which translates to higher abatement costs. This high cost reflects that the region or enterprise has already achieved significant emission reductions through efficient technologies and Management practices, thereby demonstrating superior environmental performance. Carbon abatement cost in China exhibits a trend that first decreases and then increases over this period. Before 2013, the carbon abatement cost declined, suggesting a potential deterioration in China's environmental conditions. This decline could indicate that pollution emissions were not effectively controlled and that ecological protection measures were insufficient. Contributing factors might include energy structure, industrial restructuring, technological advancements, and environmental policies. Notably, China's CAC was relatively high in 2000, reflecting heightened sensitivity to carbon emissions during the country's economic development. A sharp decrease occurred in 2002, possibly linked to the significant rise in Manufacturing exports at that time. After reaching its lowest point in 2013, the Carbon abatement cost began a gradual upward trend. This aligns with findings from Nie (2018), who observed a similar U-shaped pattern in the CAC from 2000 to 2015, with a decrease from 2000 to 2008 followed by an increase from 2009 to 2015. Although the specific periods of the studies differ, the general trend in the CAC is comparable.

Figure 2 depicts the evolution of carbon abatement cost across four regions in China—East, Northeast, West, and Central—spanning the years

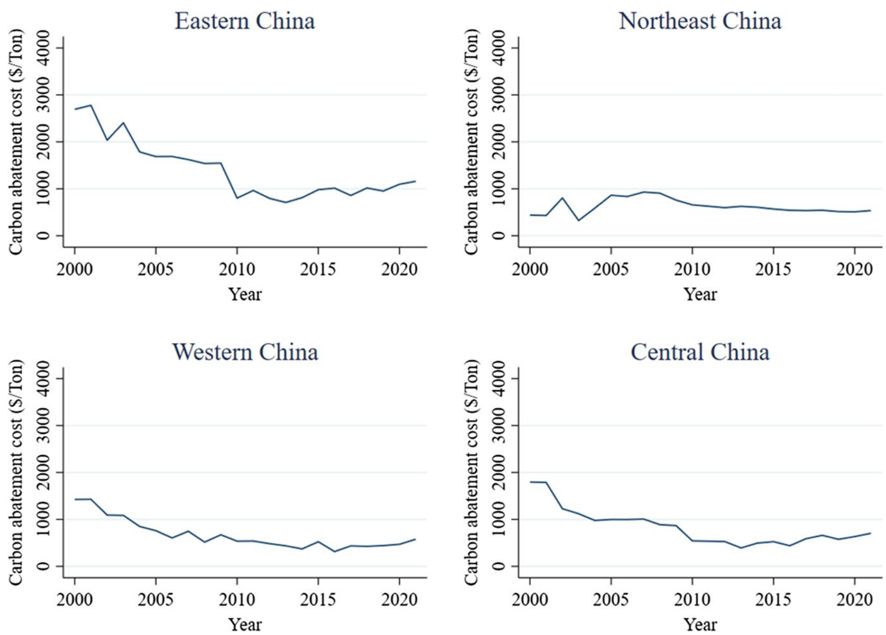

Fig. 2 Carbon abatement cost (USD/ton) by region

2000 to 2021. The Eastern region consistently shows significantly higher carbon abatement cost compared to the others, with the Central region following closely behind. The disparity can be ascribed to the diminished levels of pollution reported in the Eastern and Central China, which can be linked to their more sophisticated economic growth and advances in technology. The CAC has a U-shaped pattern across the Eastern, Western, and Central China in terms of trends. In contrast, the Northeast region shows an initial increase followed by a plateau. The unique trend in the Northeast May be Linked to its gradual transition from a heavy industrial base following the reform and opening-up policy. With the revitalization initiatives that began in the early 2000s, the Northeast focused on industrial restructuring and technological innovation. These efforts improved environmental conditions and contributed to the observed rise in carbon abatement cost. Some studies have shown that abatement cost positively

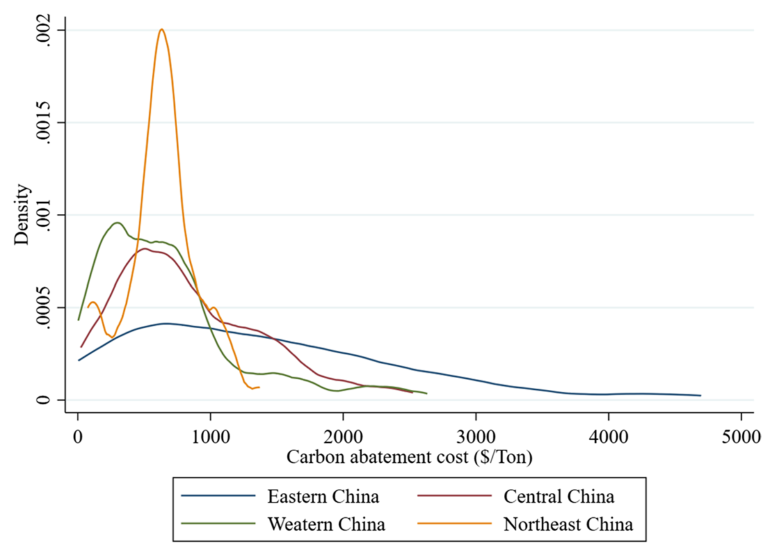

Fig. 3 Kernel density plots of subregional carbon abatement cost for all years

correlate with regional economic development, with high-income regions having significantly higher abatement cost than low-income regions (Zhang et al., 2014). This view is validated in this study. In other studies, such as Xu et al. (2023), an empirical survey of China's 31 provinces found that the upward trend in agricultural CAC in the eastern region significantly exceeds the national average. In contrast, the increase in agricultural CAC in Central and Western China is less pronounced than the national level. This suggests that although China's agricultural environmental conditions have generally improved over time, the pace of pollution management in these regions has lagged the national trend. Overall, these findings align closely with the results of our study.

The kernel density plot of carbon abatement cost in Fig. 3 reveals that the Central region has the highest peak, indicating the highest concentration of carbon abatement cost, albeit at a lower level. In contrast, the Eastern region shows the lowest peak, suggesting a more dispersed distribution of carbon abatement cost with significant regional variation. Additionally, the Central, Western, and Northeastern regions each exhibit two peaks, reflecting two distinct concentration trends, whereas the Eastern region displays only a single concentration trend.

The influence of digital technology on the carbon abatement cost

Baseline model

This research employs a two-way fixed effects model to estimate the relationship between carbon abatement cost and digital technology. The dependent variable, Carbon abatement cost, and the control variables are included in the model in logarithmic form. Table 3 displays the regression findings. The first column shows the results without control variables, while the second column shows the results with control variables.

The estimates for the degree of digitization as Main explanatory variables show a positive and significant association with carbon abatement cost at the 1% level. This suggests that a greater level of digitization is Linked to a higher cost of reducing carbon emissions. More precisely, for every additional unit of imported industrial robots, there is a corresponding rise of 1.8% per ton in the cost of reducing carbon emissions. This positive correlation suggests that digitization, driven by diverse technological advancements, enhances the effectiveness of carbon reduction efforts and thereby improves environmental performance (Cheng et al., 2024). The results align

Table 3 Impact of digitization on the cost of reducing carbon emissions: baseline model

Variable	(1) Logged Carbon abatement cost	(2) Logged Carbon abatement cost
Degree of digitization	0.022***	0.018***
	(0.007)	(0.007)
Ln Value added of secondary industry		−0.913***
		(0.256)
Ln Oil consumption		−0.007
		(0.137)
Ln Clean energy generation		0.049
		(0.053)
Ln Labor of secondary industry		0.034
		(0.180)
Constant	6.422***	12.203***
	(0.028)	(1.937)
Observations	660	660
R-squared	0.615	0.623
Country FE	Yes	Yes
Year FE	Yes	Yes

Standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

with previous studies, such as the work by Zeng and Yang (2023), who used panel data from 30 Chinese provinces (including municipalities and autonomous regions) from 2010 to 2020. Their research empirically demonstrated that the digitalization of tax administration significantly reduces carbon emissions, confirming that digital technology plays a positive role in carbon reduction.

From a theoretical perspective, digital technology can improve energy efficiency and optimize resource allocation, leading to more effective carbon reduction. For example, industrial robots and artificial intelligence can improve production efficiency and reduce waste, leading to lower carbon emissions (Li et al., 2025; Yan & Sun, 2025). Moreover, digital technology can also drive the development of high-tech industries that are less energy-intensive and more environmentally friendly (Wan et al., 2023). These industries often have a higher proportion of clean energy use and innovative technologies, which further contribute to the reduction of carbon emissions.

Regarding control variables, value added by the secondary industry shows a significantly negative relationship with the carbon abatement cost at the 1% level. This indicates that as the secondary sector develops, environmental pollution intensifies. Manufacturing and industrial production processes often generate pollutants such as wastewater, exhaust gases, and solid waste. As environmental pollution increases, the potential for carbon reduction grows, making relative carbon reduction easier and resulting in a lower carbon abatement cost (Ji & Zhou, 2020).

To further validate the robustness of our results, we conducted additional analyses using alternative measures of digitization. Specifically, we employed three different metrics of industrial robot intensity: (1) the ratio of industrial robots to labor, (2) the ratio of industrial robots to the value added in the secondary industry, and (3) the ratio of industrial robots to total GDP. Utilizing these alternative definitions enabled us to assess the consistency of our findings across various measures of industrial robot deployment.

The results in Table 4 show that the degree of digitization remains significantly and positively associated with carbon abatement cost across all three specifications. Specifically, the coefficients for the degree of digitization are 0.094, 0.447, and 1.196 for the three measures, respectively. This consistency across different definitions of industrial robots reinforces the robustness of our findings.

Table 4 Robust check: Robot intensity

Variable	Logged Carbon abatement cost		
	Robot intensity_labor	Robot intensity_secondgdp	Robot intensity_gdp
Degree of digitization	0.094***	0.447***	1.196***
	(0.027)	(0.118)	(0.342)
Ln Value added of secondary industry	−0.926***	−0.835***	−0.846***
	(0.254)	(0.257)	(0.257)
Ln Oil consumption	−0.015	−0.018	−0.015
	(0.137)	(0.137)	(0.137)
Ln Clean energy generation	0.059	0.051	0.045
	(0.053)	(0.053)	(0.053)
Ln Labor of secondary industry	0.081	0.101	0.073
	(0.181)	(0.181)	(0.180)
Constant	12.009***	11.324***	11.575***
	(1.927)	(1.956)	(1.951)
Observations	660	660	660
R-squared	0.626	0.627	0.626
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Standard errors in parentheses; ***$p<0.01$, **$p<0.05$, *$p<0.1$

Table 5 Robust check: Lagged term of degree of digitization

Variable	(1) Logged Carbon abatement cost	(2) Logged Carbon abatement cost	(3) Logged Carbon abatement cost
Degree of digitization (1 year lag)	0.019**		
	(0.008)		
Degree of digitization (2 years lag)		0.017**	
		(0.009)	
Degree of digitization (3 years lag)			0.012
			(0.009)
Ln Value added of secondary industry	−0.756***	−0.645**	−0.498*
	(0.268)	(0.282)	(0.288)
Ln Oil consumption	0.035	0.138	0.021
	(0.145)	(0.150)	(0.150)
Ln Clean energy generation	0.101*	0.153***	0.154**
	(0.056)	(0.059)	(0.060)
Ln Labor of secondary industry	0.147	0.233	0.359*
	(0.187)	(0.194)	(0.196)
Constant	9.882***	7.630***	6.610***
	(2.047)	(2.156)	(2.192)
Observations	630	600	570
R-squared	0.623	0.624	0.637
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

To account for potential time-lagged effects of digitization on carbon abatement cost, we included one-year, two-year, and three-year lagged terms of the degree of digitization in our model. This robustness check helps to determine whether the impact of digitization on carbon abatement cost persists over time.

Table 5 presents the results using lagged terms of the degree of digitization. The coefficients for the first- and second-order lagged terms are positive and significant 0.019 and 0.017, respectively, while the third-order lagged term is not significant. This suggests that the impact of digitization on carbon abatement costs is more pronounced in the short to medium term, possibly due to the time required for digital technologies to be fully integrated into production processes and for their benefits to be realized.

To address potential biases arising from outliers and ensure that our results are not driven by extreme values, we conducted robustness checks using sample trimming. Specifically, we trimmed the top 5%, 10%, and 15% of the data to exclude potential outliers. This approach helps verify whether the observed effects are robust to the presence of extreme values in the dataset. The results in Table 6 show that the degree of digitization remains significantly and positively associated with carbon abatement cost across all three trimmed samples. Specifically, for the 5% trimmed sample, the coefficient for the degree of digitization is 0.054; for the 10% trimmed sample, the coefficient is 0.043; for the 15% trimmed sample, the coefficient is 0.072.

These consistent results across different levels of sample trimming further confirm the robustness of our findings. The significant positive association between the degree of digitization and carbon abatement cost persists even after excluding potential outliers, indicating that our results are not driven by extreme values.

Mechanism analysis

To further explore the underlying mechanisms through which digitization affects carbon abatement costs, we employ a mediation effect model to examine the role of energy utilization efficiency. Energy utilization efficiency is measured as the amount of carbon dioxide emitted per unit of secondary industry GDP (i.e., variable "Energy efficiency"). It is important to note that

Table 6 Robust check: Sample trimming

Variable	Logged Carbon abatement cost Trimmed_5%	Trimmed_10%	Trimmed_15%
Degree of digitization	0.054***	0.043***	0.072***
	(0.013)	(0.009)	(0.022)
Ln Value added of secondary industry	−0.721***	−0.729***	−0.688***
	(0.199)	(0.212)	(0.191)
Ln Oil consumption	−0.048	−0.059	−0.045
	(0.107)	(0.113)	(0.102)
Ln Clean energy generation	0.019	0.017	0.012
	(0.041)	(0.044)	(0.039)
Ln Labor of secondary industry	0.005	0.030	0.019
	(0.140)	(0.149)	(0.133)
Constant	11.493***	11.470***	11.201***
	(1.514)	(1.612)	(1.466)
Observations	660	660	660
R-squared	0.697	0.687	0.699
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 7 Mechanism test: Energy utilization efficiency

Variable	(1) Energy efficiency	(2) Logged Carbon abatement cost
Degree of digitization	−0.009***	0.015**
	(0.002)	(0.007)
Energy efficiency		−0.358**
		(0.145)
Ln Value added of secondary industry	−0.107	−0.952***
	(0.072)	(0.256)
Ln Oil consumption	−0.042	−0.022
	(0.038)	(0.137)
Ln Clean energy generation	0.018	0.055
	(0.015)	(0.053)
Ln Labor of secondary industry	0.120**	0.077
	(0.050)	(0.180)
Constant	0.513	12.386***
	(0.541)	(1.930)
Observations	660	660
R-squared	0.757	0.627
Country FE	Yes	Yes
Year FE	Yes	Yes

Standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

a lower value of "Energy efficiency" indicates higher energy utilization efficiency, meaning that less carbon dioxide is emitted for each unit of secondary industry GDP produced.

Table 7 presents the results of the mediation effect model, which is divided into two columns: Column (1) examines the impact of digitization on energy utilization efficiency, while Column (2) investigates the combined effect of digitization and energy utilization efficiency on carbon abatement costs.

The results in Column (1) indicate that digitization has a negative and statistically significant effect on carbon dioxide emissions per unit of secondary industry GDP, with a coefficient of −0.009. This suggests that as digitization advances, carbon emissions relative to economic output decrease, reflecting an improvement in energy utilization efficiency. In other words, digitalization promotes more efficient energy use, consistent with the expectation that digital technologies optimize production processes and reduce energy waste.

In Column (2), we introduce energy utilization efficiency as a mediating variable to examine its role in the relationship between digitization and carbon abatement costs. The results show that energy utilization efficiency has a negative and statistically significant effect on carbon abatement costs, with a coefficient of −0.358. This suggests that higher energy efficiency (i.e., lower carbon emissions per unit of secondary industry GDP) is associated with lower carbon abatement costs. This finding aligns with the intuition that more efficient energy use reduces the need for costly carbon mitigation measures.

The mediation effect model reveals that energy utilization efficiency plays a significant role in the relationship between digitization and carbon abatement costs. Specifically, digitization improves energy efficiency, which in turn increases carbon abatement costs.

Heterogeneity analysis

To explore the regional differences in the impact of digitization on carbon abatement cost, we conducted a heterogeneity analysis across four major regions in China: Eastern China, Central China, Western China, and North-eastern China. The results reveal significant regional differences in the impact of digitization on carbon abatement cost. As shown in Table 8, the impact of digitization is most pronounced in Central China, where higher levels of digitization are significantly associated with higher carbon abatement costs, with a coefficient of 0.975. In contrast, the effects of digitization in Eastern China, Western China, and North-eastern China are less significant.

This pattern suggests that while digitization has a notable impact on carbon abatement cost in Central China, its influence in other regions is relatively

Table 8 Impact of digitization on the cost of reducing carbon emissions: heterogeneity across regions

Variable	(1) Eastern China	(2) Central China	(3) Western China	(4) North-eastern China
Degree of digitization	0.013	0.975**	−0.070	0.058
	(0.009)	(0.450)	(0.184)	(0.035)
Ln Value added of secondary industry	−0.916	−0.252	−0.619	1.322**
	(0.858)	(0.762)	(0.412)	(0.610)
Ln Oil consumption	−1.038**	−0.094	0.195	−2.888***
	(0.448)	(0.389)	(0.195)	(0.493)
Ln Clean energy generation	0.136*	−0.413***	−0.067	0.822*
	(0.072)	(0.134)	(0.131)	(0.452)
Ln Labor of secondary industry	−1.323***	2.186***	0.384*	−3.618***
	(0.472)	(0.587)	(0.231)	(1.318)
Constant	28.512***	−3.872	7.033**	33.368***
	(7.578)	(6.787)	(3.159)	(6.930)
Observations	220	132	242	66
R-squared	0.674	0.675	0.696	0.758
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

weaker. The significant effect in Central China may be attributed to the region's unique characteristics. Central China has experienced rapid industrialization and urbanization, leading to substantial investments in digital infrastructure and advanced technologies (Javaid et al., 2022). These investments, while enhancing productivity and efficiency, also result in higher initial costs for carbon abatement efforts. Additionally, Central China's role as a major industrial hub means that the region faces higher baseline carbon emissions, making the impact of digitization on abatement costs more pronounced (Ren et al., 2023).

In contrast, Eastern China, despite its advanced economic development and technological adoption, shows an insignificant effect of digitization on carbon abatement cost. This could be due to the region's early adoption of digital technologies, which may have already optimized energy efficiency and carbon reduction efforts, leaving less room for additional gains. Western China and North-eastern China, on the other hand, show even smaller or negative effects, which may reflect different economic structures and policy focuses. Western China's focus on resource-intensive industries and North-eastern China's historical reliance on heavy industry may limit the immediate impact of digitization on carbon abatement costs.

These findings underscore the importance of region-specific policies and strategies to effectively manage the transition to a low-carbon economy. Policymakers should consider the unique characteristics and needs of each region when designing policies aimed at reducing carbon emissions through digitization. For instance, Central China may require targeted investments in advanced digital technologies and support for high-tech industries to mitigate the initial costs associated with carbon abatement. Meanwhile, Eastern China could focus on further optimizing existing digital infrastructure to enhance carbon reduction efforts. Future research should further explore the underlying mechanisms driving these regional differences and identify targeted interventions to optimize the benefits of digitization for carbon abatement efforts across different regions.

Discussion

This study develops a comprehensive model to estimate CAC and analyze the impact of digital technology on CAC across different regions in China. We advanced the carbon shadow pricing literature by explicitly modeling clean and fossil energy sources separately. This approach provides a more realistic framework compared to earlier studies that treat energy consumption as a single aggregated input, thereby overlooking substantial differences in carbon emission intensity and environmental impacts across energy types (Cui et al., 2022). Examining the dynamics of China's carbon abatement cost from 2000 to 2021, we observe a decline in CAC prior to 2013 followed by a subsequent increase. These patterns align with the findings of Nie (2018), reinforcing evidence that China's environmental performance has improved over time despite initial difficulties in controlling pollution emissions.

The baseline model results demonstrate that digitalization exerts a positive and statistically significant effect on CAC, indicating that higher levels of digital adoption are associated with increased costs of reducing carbon emissions. This finding is consistent with prior research (e.g., Zeng & Yang, 2023) and underscores the pivotal role of advanced digital technologies—such as the Internet of Things (IoT) and artificial intelligence (AI)—in enhancing energy efficiency and lowering carbon emissions per unit of output (Yi et al., 2022; Yan et al., 2023).

Robustness checks, including alternative proxies for robot intensity, the inclusion of lagged digitalization terms, and sample trimming, consistently confirm the positive and significant relationship between digitalization and CAC. These tests validate that our results are robust across various operationalizations of digitalization and are not driven by outliers or short-term fluctuations. Furthermore, mediation analysis reveals that digitalization enhances energy utilization efficiency, which in turn raises carbon abatement costs. This finding highlights the critical mediating role of energy efficiency in linking digitalization to carbon abatement efforts (Gao et al., 2022).

The heterogeneity analysis reveals that the impact of digitalization on CAC varies markedly across regions, with the strongest effects observed in Central China. This finding reflects the region's rapid industrialization and recent investments in digital infrastructure, which amplify the efficiency gains from digital adoption. In contrast, Eastern China, despite its more advanced economic development, exhibits a weaker effect, likely due to early adoption and the saturation of digital technologies, resulting in diminishing marginal returns. Western and Northeast China show even smaller or, in some cases, negative effects, which may stem from distinct economic structures, lower levels of digital readiness, or divergent policy priorities (Javaid et al., 2022; Ren et al., 2023). These results suggest that initial conditions, such as the baseline level of economic development and digital capacity, play a critical role in shaping the effectiveness of digitalization on carbon abatement.

Our findings diverge from and extend existing literature in several ways. Unlike studies that aggregate energy sources into a single variable (Cui et al., 2022), we demonstrate that disaggregating clean and fossil energy sources provides a more accurate assessment of CAC. This methodological innovation aligns with the growing emphasis on clean energy in achieving sustainable development goals (Murshed et al., 2021). Additionally, while prior research highlights digitization's potential to reduce emissions (Zeng & Yang, 2023), our analysis reveals its role in increasing CAC by enhancing the precision and effectiveness of carbon reduction efforts. This nuanced understanding fills a critical gap in the literature and provides a foundation for future research on the interplay between digital technologies and carbon abatement strategies.

Conclusions and policy recommendations

This study advances the estimation of carbon abatement costs (CAC) by introducing a novel framework that disaggregates clean and fossil energy sources, capturing their distinct carbon intensities and environmental impacts. This approach yields more precise CAC estimates compared to traditional models that aggregate energy inputs, offering deeper insights into the economic trade-offs involved in energy transitions.

Our empirical analysis reveals a nuanced role of digital technology: higher levels of digitalization are associated with increased measured CAC. This result does not imply inefficiency but reflects the progression toward deeper decarbonization, where digital tools enhance energy efficiency and eliminate low-cost abatement opportunities, thereby raising the marginal cost of further emission reductions. Mediation analysis confirms that improvements in energy utilization efficiency largely drive this relationship. Furthermore, significant regional heterogeneity exists, with the strongest digitalization effects on CAC in Central China—likely due to ongoing industrialization and higher baseline emissions—while Eastern China shows diminishing returns consistent with its advanced digital infrastructure.

Building on these findings, we offer several policy recommendations. The persistent gap between estimated CAC and carbon market prices indicates systemic inefficiencies that policymakers should address by phasing out free allowances, implementing auction-based mechanisms, and expanding market coverage to underrepresented sectors. The higher CAC observed for clean energy underlines the importance of targeted subsidies and tax incentives to accelerate clean energy adoption, especially in heavy industry regions. Moreover, investing in digital infrastructure is crucial to optimize energy use and reduce waste, particularly in regions with high emissions and lower digital readiness.

In sum, this study provides a refined understanding of CAC by differentiating energy types and highlights digital technology's critical role in shaping carbon abatement costs and pathways. The findings support policy efforts that align carbon pricing with true social costs and advocate for regionally tailored digital and environmental strategies to effectively advance China's—and potentially other countries'—low-carbon transitions. Future research should extend this framework to international contexts and explore interactions between digitalization and other structural determinants of carbon abatement.

Limitations and directions for future research

This study has several limitations that future research should address. First, our reliance on provincial-level data may obscure important variations in environmental performance within provinces. Future studies should leverage more granular data at the city or firm level to better capture these dynamics and provide deeper insights into the determinants of carbon abatement costs across different contexts. Second, while our analysis focuses primarily on the impact of digital technology, it does not fully account for potential interactions with other influential factors such as regulatory stringency, foreign investment, and economic structure. Incorporating multivariate frameworks that isolate and examine these interactions would offer a more comprehensive understanding of the drivers of carbon abatement costs. Third, our study centers on China, which may limit the generalizability of the findings. Expanding the scope to include comparative analyses across emerging and developed economies could enhance external validity and shed light on how digital technology and other factors influence environmental performance globally.

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Declarations

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