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DIGITAL ECONOMY AND CARBON EMISSIONS: SPATIAL SPILLOVER EFFECT AND INDUSTRIAL STRUCTURE MEDIATION EFFECT IN CHINA

Yuxi CHEN[1]✉, Jian LIU[2]

[1] *College of Economics and Management, Nanjing University of Aeronautics and Astronautics, Nanjing, China*
[2] *College of Economics, Beijing Wuzi University, Beijing, China*

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Abstract. The relationship between the digital economy and carbon emissions has emerged as a critical issue in the pursuit of the Sustainable Development Goals by 2030. This study examines the spatial spillover effects and the mediating role of industrial structure in this relationship using panel data from 285 prefecture-level cities in China between 2011 and 2022. Employing the Spatial Durbin Model (SDM) to capture spatial effects, stepwise regression and bootstrap tests for mediating effects, and the System Generalised Method of Moments (SYS-GMM) to address endogeneity, the study reveals several key findings. First, the digital economy significantly increases carbon emissions with substantial spillover effects across regions. Second, carbon emissions exhibit both temporal and spatial dependence, influenced by time and location, with emissions in neighboring areas having a significant impact, leading to a "snowball" effect. Third, the digital economy indirectly elevates carbon emissions by optimizing industrial structures. These findings underscore the need for comprehensive strategies to manage carbon emissions effectively during economic transformation, aiming towards an environmentally sustainable economy.

Keywords: digital economy, carbon emission, mediating effect of industrial structure, spatial spillover effect.

JEL Classification: F63, O44.

✉Corresponding author. E-mail: *yuxichendjj@outlook.com*

1. Introduction

The interplay between the digital economy and carbon emissions presents a complex and pressing challenge in the context of global sustainable development. As the digital economy grows, characterized by advancements in information technology, increased internet usage, and the proliferation of digital services, its impact on carbon emissions has become a focal point of scholarly debate. On one hand, the digital economy can drive efficiency and innovation, potentially reducing emissions through improved resource management and lower energy consumption. On the other hand, the expansion of digital infrastructure, increased energy demands from data centers, and the proliferation of electronic devices contribute to higher carbon emissions. This dual effect creates a paradox where the digital economy, while fostering economic growth and development, simultaneously exacerbates environmental challenges. Moreover, the spatial distribution of these effects is uneven, with some regions experiencing more significant impacts due to varying levels of digital economy development and industrial activities. This spatial heterogeneity complicates the formulation of effective policies, as strategies that work in one region may not be applicable in another. Additionally, the relationship between the digital economy and carbon emissions is mediated by changes in industrial structure, where shifts towards more or less carbon-intensive industries can influence overall emission levels. Understanding these dynamics is crucial for developing targeted interventions that balance economic growth with environmental sustainability, ensuring that the benefits of the digital economy do not come at the expense of the planet's health.

The rapid development of the digital economy has fundamentally transformed various aspects of society, driving significant economic growth and innovation. As digital technologies become increasingly integrated into everyday life and business operations, their impact on carbon emissions has attracted substantial scholarly attention. The digital economy, encompassing advancements in information technology, the proliferation of digital services, and widespread internet use, presents a paradoxical relationship with carbon emissions (Xie et al., 2022). While it promotes efficiency and resource optimization, potentially reducing emissions in some areas, it also leads to increased energy consumption and emissions from data centers, electronic devices, and supporting infrastructure. This dual effect necessitates a nuanced understanding of the digital economy's overall impact on the environment. Previous studies have highlighted the importance of examining this relationship in the context of spatial and industrial structures. For instance, (Yiming et al., 2024) found that regions with more advanced digital economies tend to exhibit higher carbon emissions due to increased energy demands. Similarly, (Shi & Umair, 2024) demonstrated that the industrial structure plays a critical mediating role, where shifts towards high-tech and service-oriented industries can either mitigate or exacerbate carbon emissions depending on their energy profiles. Understanding the spatial spillover effects is also crucial, as emissions in one region can influence neighboring areas, creating a "snowball" effect (Xinxin et al., 2024). Therefore, research on the relationship between the digital economy and carbon emissions is vital for formulating effective policies that promote sustainable economic growth while minimizing environmental impact.

Anthropogenic climate warming has engendered profound ramifications for human society. Dilanchiev et al. (2024) elucidates that climatic perturbations have ensnared approximately 9% of the global populace – translating to over 600 million individuals – in the throes of severe ecological vicissitudes. These challenges encompass a gamut of concerns, ranging from physiological health and the caliber of life, to agriculture, ecosystems, and the intricate fabric of societal and political structures. For instance, periods of extreme thermal elevation have been correlated with an uptick in mortality, a diminution in labor productivity, impediments to cognitive development, and adverse perinatal outcomes. Moreover, the insidious rise in sea levels, precipitated by the greenhouse effect, coupled with the increased incidence of fluvial disasters and the proliferation of pests and pathogens, poses a formidable threat to the stability of agriculture and ecosystems. In the socio-political realm, the accelerative forces of climate change have the potential to intensify societal strife, propagate hate speech, catalyze mass migrations, and fuel the widespread dissemination of infectious diseases, thereby challenging the bedrock of social equanimity and international diplomacy (Wang et al., 2024). The current trajectory of policy and praxis, if unaltered and devoid of further intervention, portends a temperature elevation of approximately 2.7 °C by the terminus of the current century. Such a climatic shift implies that a substantial fraction – between 22% to 39% – of humanity will be precariously positioned outside the climatic niches conducive to life. However, a mitigation of warming to a ceiling of 1.5 °C would markedly reduce the demographic exposed to extreme temperatures by a factor of five (Li et al., 2023a). Given the central role of greenhouse gases in global warming, there is an exigent imperative for the international community to halve emissions within the impending decade and to strive for a net-zero carbon dioxide emission status by mid-century.

In the face of the escalating challenge posed by global climate warming, governments around the world, alongside international bodies, have crafted a suite of policies and pledges to confront this existential threat. A pivotal manifestation of these concerted efforts was the United Nations Climate Change Conference (COP26) (United Nations Climate Change, 2021) held in Glasgow, United Kingdom in November 2021. The quintessence of this congregation was the upholding of the commitments to sustainable development as enshrined in the Paris Agreement and the United Nations Framework Convention on Climate Change (UNFCCC), with a particular emphasis on the imperative of constraining the rise in global temperatures to within 1.5 °C above pre-industrial levels (Zheng & Wong, 2024). Within this contingent, 58 nations – which collectively are accountable for more than half of global emissions – have avowed their intention to achieve net-zero emissions by the year 2050 (Mohsin et al., 2023). Notably, China, regarded as one of the most prodigious contributors to global pollution, has emissions of carbon dioxide (CO_2) that surpass the cumulative output of all developed countries. Around the year 2020, China's CO_2 emissions reached a staggering 9.89 billion tons, accounting for approximately 30% of the world's total CO_2 emissions (Yuan et al., 2023). As the world's foremost emitter of CO_2, China has taken the significant step of ratifying the Paris Agreement under the aegis of the UNFCCC, and has pledged to implement CO_2 emission reduction strategies to meet its climate change mitigation targets. Furthermore, China has ambitiously committed to peak its carbon emissions by 2030, with the aim of achieving carbon neutrality by the year 2060. These pledges underscore a global movement towards an era of environmental accountability and resilience, with the international community forging a path to a sustainable future (Wu et al., 2023).

This study makes a significant contribution to the existing literature by providing a comprehensive analysis of the impact of the digital economy on carbon emissions, specifically within the context of China's rapidly evolving urban landscapes. The study is distinctive in its use of panel data from 285 prefecture-level cities in China over an extensive period, from 2011 to 2019. This time frame allows for a nuanced understanding of the trends and patterns over almost a decade, a period marked by significant technological advancements and economic shifts. The utilization of the Spatial Durbin Model (SDM) in this study is particularly noteworthy. By employing SDM, the study offers valuable insights into the spatial spillover effects of the digital economy on carbon emissions, an aspect often overlooked in conventional models. Additionally, the study's application of stepwise regression methods and bootstrap tests to investigate mediating effects sheds light on the indirect pathways through which the digital economy influences carbon emissions. This approach enables a more detailed exploration of the underlying mechanisms, contributing to a deeper understanding of the complex interplay between economic development and environmental impact. Furthermore, the use of the System Generalized Method of Moments (SYS-GMM) to address endogeneity concerns enhances the robustness of the findings. This methodological choice is crucial in establishing the causal relationships in the data, thereby strengthening the study's contribution to the literature on environmental economics and policy. In summary, the study's contribution to the literature is multifaceted, offering not only a detailed empirical analysis over a significant time period but also methodological advancements in understanding the environmental impacts of the digital economy. Its findings provide valuable insights for policymakers and scholars interested in balancing economic growth with environmental sustainability.

The remainder of this study is structured as follows. Section 2 presents a comprehensive review of the literature. Section 3 delineates the research methodology and sources of data. Section 4 discusses the findings and deliberations, encompassing the selection of a spatial Durbin model with time-invariant fixed effects, benchmark regression analyses, mediation effects, and spatial spillover implications. Section 5 is dedicated to robustness checks and subsample regressions. Finally, Section 6 encapsulates the conclusions and policy implications.

2. Literature review

2.1. Correlation between digital economy and carbon emission

Within the realm of environmental economics, the regulation of carbon emissions stands as a pivotal concern. Scholarly inquiries have identified a multitude of salient factors influencing carbon emissions, among which are economic development , urbanization, industrial agglomeration and infrastructural development (Ma et al., 2022a). Nonetheless, the meteoric rise and pervasive diffusion of internet technologies have catalyzed an increase in the digital economy's share of the global economic aggregate. This trend has kindled widespread contemplation and scholarly pursuit regarding the digital economy's impact on climate change and sustainability issues (Zhu & Chen, 2022). Indeed, contemporary research has begun to pivot towards elucidating the nexus between the digital economy and carbon emission, swiftly ascending as a research focal point. Liu et al. (2023b) even posits that, in comparison to the traditional economy, the digital economy is more eco-conscious during its production processes, with a marked reduction in energy consumption and environmental emissions.

Within the scholarly discourse on the carbon mitigation impact of the digital economy, three predominant perspectives emerge. The first predominant posits that the digital economy exerts a notable decarbonization effect. Liu and Chen (2022) investigate the mechanisms by which the digital economy influences carbon emissions, examining the dynamic impacts of Information and Communication Technology (ICT) on economic and energy systems. They contend that the digital economy can diminish carbon emissions through several avenues, including augmenting energy efficiency, transforming consumption patterns, and fostering green growth. Firstly, the digital economy has the potential to enhance energy efficiency. Jiang et al. (2023) leverage panel data from 277 Chinese cities spanning 2011 to 2019 and discover that the digital economy contributes to a reduction in both the intensity and the aggregate of energy consumption, as well as to an increase in urban greenery coverage, which, in turn, curtails carbon dioxide emissions. Additionally, the application of digital technology in the energy sector has catalyzed innovation in energy technology, thereby improving the efficiency of energy utilization. Secondly, the digital economy is capable of altering consumer habits. Novel digital economic paradigms, such as intelligent buildings, telecommuting, and optimized manufacturing processes can reduce unnecessary transportation and its associated emissions by changing the way residents work. Moreover, digital technology can promote the dematerialization and intelligentization of residents' work and lifestyles, which aids in lowering their energy demands (Chen et al., 2023), for example, through the intelligent design of residential buildings and domestic appliances. Furthermore, research by Ma et al. (2022b) indicates that during the COVID-19 pandemic, digital technology enabled the transition of residents' offline activities to online platforms, thereby reducing energy consumption and potentially contributing to carbon abatement. Thirdly, the digital economy can propel green development. Litvinenko (2020) assert that the evolution of ICT has a significant positive impact on the green economy. The research by Martynenko and Vershinina (2018) suggests that digitalization has led to the ecological modernization of production, which not only ensures the conservation of various resources but also underpins the sustainable development of territories, nations, and regions.

Conversely, the second perspective posits that the digital economy exacerbates carbon emissions. The world's top ten economies in 2019, arriving at the conclusion that digitization has not facilitated the advancement of a green or energy-efficient economy; rather, it has impeded such progress, culminating in an escalation of carbon dioxide emissions. Similarly, Murshed (2020) inspected trade openness data in information and communication technology (ICT) among South Asian economies, discerning that greater ICT trade openness does not translate to carbon emission reductions. Utilizing annual data from Australia spanning from 1985 to 2012, Huang et al. (2022) employed an array of econometric techniques to estimate the impact of internet usage and economic growth on electricity consumption. Their findings suggest that internet usage stimulates an increase in electricity demand, which is counterproductive to carbon emission reduction efforts.

The theoretical foundation for the hypothesis that the digital economy increases carbon emissions can be derived from several economic and environmental theories. The Environmental Kuznets Curve (EKC) hypothesis, for instance, suggests that in the early stages of economic development, environmental degradation and pollution increase, including carbon emissions. As the economy grows, income levels rise, and eventually, technological advancements and structural changes lead to a decrease in pollution levels. However, the initial stages of digital economic development are likely to involve significant investments in digital infrastructure, such as data centers, communication networks, and manufacturing of electronic devices, which are energy-intensive and contribute to higher carbon emissions (Yu et al., 2023). Moreover, the rebound effect theory posits that increases in energy efficiency from technological advancements can lead to increased energy consumption due to behavioral or other systemic responses (Cui et al., 2023). In the context of the digital economy, while digital technologies may improve energy efficiency, they also enable increased economic activities and consumption patterns that can offset these efficiency gains and result in higher overall energy demand and carbon emissions. The scale effect, often discussed in environmental economics, further supports this hypothesis. As digital technologies lower production costs and create new economic opportunities, they can lead to an expansion in economic activities, thereby increasing the total energy consumption and associated carbon emissions (Li & Umair, 2023a). This is particularly evident in sectors such as cloud computing, e-commerce, and digital entertainment, where the demand for data processing and storage grows exponentially, leading to greater energy consumption. Additionally, the structural effect highlights that the digital economy can lead to changes in industrial structure, potentially increasing the share of energy-intensive industries if digital technologies primarily boost sectors such as information technology hardware manufacturing, which is known for high energy consumption and carbon emissions (Liu et al., 2023a). In summary, while the digital economy has the potential to enhance energy efficiency and promote green growth, theoretical and empirical evidence suggests that it may initially lead to higher carbon emissions due to increased energy demands, the rebound effect, and changes in industrial structure. This hypothesis aligns with the Environmental Kuznets Curve, the rebound effect theory, and the scale and structural effects in environmental economics.

H1: *The digital economy contributes to an increase in carbon emissions.*

2.2. Intermediary effect

Numerous scholars contend that the digital economy has the potential to augment the proportion of the tertiary sector within the overall industrial structure. Firstly, the digital economy catalyzes the optimization and transformation of industrial composition through the acceleration of technological advancement and innovation. For the tertiary sector in particular, such innovation and technological progress not only enhance production efficiency of tertiary sector and reduce relative costs as indicated by Ma et al. (2022b), but also fortify the competitive advantage and growth of high-tech industries – especially those within the tertiary sector – thereby driving a shift in industrial structure. The research by Li et al, (2021a) suggests that the evolution of the digital economy fosters the integration of innovative resources across regions, encompassing capital, talent, and technological elements, positioning the digital economy as superior in terms of technological and innovative capabilities when compared to other economic forms. Furthermore, the synergy between the digital economy and the tertiary sector surpasses that of its integration with the traditional manufacturing sector, as exemplified by the interconnected logistics and computer services provided by big data platforms. This implies that the contribution of the digital economy to the growth of the tertiary sector often exceeds that of the secondary sector, facilitating an increased share and refinement of the tertiary sector within the industrial framework. Moreover, the highly technological and innovative nature of the digital economy has also given rise to new industries and business models. These emerging sectors offer a plethora of employment and educational opportunities, and afford entrepreneurs more convenient access to innovative resources, as seen in the sharing economy, online education, and telemedicine (He et al., 2022). Industries centered around artificial intelligence, big data, and fifth-generation mobile communications technology not only serve as the foundation for corporate digital transformation but also support the emergence of new industrial spheres (Kochergin, 2021). In the case of the traditional manufacturing sector, or secondary industry, innovation and technological progression are permeating the digitalization of the industry, with digital information technologies such as cloud computing and big data gradually integrating into the production processes, organizational structures, and business promotions of traditional industries. This has not only optimized traditional business operations, enhancing production efficiency, but has also steered traditional industries towards a digital, tertiary-sector transformation, thereby increasing the tertiary sector's share. Secondly, the digital economy has the capacity to elevate collaborative efficiency. Supported by digital platforms, consumers in the tertiary sector can locate desired products and procure high-quality services at minimal costs, while producers can significantly reduce operational expenses while accessing essential development resources. Businesses, by precisely capturing consumer demand to guide production and offer customized product services, can reduce production and promotional costs, minimize inventory, and strengthen collaborative efficiency with consumers. Furthermore, in the digital era, the recombination of production elements differs from traditional patterns, with notable changes in the status of elements and new modes of integration enhancing multi-dimensional collaborative efficiency, ultimately expediting the industrial structure's transformation (Wang & Li, 2023). For traditional manufacturing, the digital economy, which primarily utilizes information and digital data as production elements, promotes the intelligent and digital transformation of enterprises during integration with traditional industries. This enables the industrial structure to shift from labor-intensive and capital-intensive industries to data-intensive and technology-intensive ones, aiding the gradual progression of the entire industrial system towards the tertiary sector. Lastly, in terms of foreign trade within an open economic model, countries tend to specialize in industries and sectors where they possess comparative advantages, and this specialization process can lead to structural changes. For developing nations, digitalization reduces the transaction costs associated with foreign trade, thereby benefiting these countries by leveraging their comparative advantages. Simultaneously, re-evaluating potential comparative advantages related to tasks, products, and sectors driven by digitalization may prove valuable, as these digitalization-driven entities exhibit higher growth rates (for instance, due to network and scale effects) compared to traditional tasks, products, and sectors (Li et al., 2021a). The cumulative disparity in growth rates ultimately results in significant shifts within the industrial structure.

H2: *The industrial structure, characterized by the increasing ratio of tertiary to secondary sector activities, serves as a mediating variable in the relationship between the digital economy and carbon emissions.*

2.3. Spatial spillover effect

The digital economy is renowned for its salient attributes such as openness, transcendence of temporal and spatial constraints, and the ethos of economic sharing. A pivotal attribute is the employment of efficacious digital platforms for the transmission of information, which not only mitigates the inherent spatial barriers and asymmetry of information among market entities but also fortifies the interconnectivity of regional economic endeavors. The evolution of the digital economy has engendered a synergistic integration of online and offline modalities. The ascent of the internet economy has attenuated the constraints of geographical proximity on the dissemination of technology and knowledge, thereby elevating the ubiquity of information and knowledge and generating pronounced spillover effects. In their pioneering study, Xing et al. (2023) discerned the spatial spillover effects engendered by the advent of information technology through their meticulous analysis of panel data across 48 states in the United States. Erwansyah (2023) delves into the discourse on the spatial dynamics of spillover effects from the perspective of knowledge and technological dissemination. The internet's influence on regional economic development manifests in various domains, including economic growth resource misallocation and digital finance all of which exhibit spatial spillover effects (Li et al., 2023a). Furthermore, a cadre of scholars has substantiated the spatial spillover effects of the digital economy on carbon emissions. For instance, He et al. (2022) conducted an empirical study using a spatial panel Durbin model on provincial-level panel data in China, revealing that the development of the digital economy significantly contributes to carbon emission reductions through spatial spillover. Skare et al. (2023) constructed a composite index of information and communication technology (ICT) vis-à-vis socio-economic development through principal component analysis (PCA) and, utilizing a spatial Durbin model (SDM), discovered that ICT's spatial spillover engendered certain adverse impacts on the socio-economic development of neighboring regions. Collectively, these studies demonstrate that the proliferation of the digital economy not only exerts influence within its immediate locale but also diffuses through various mechanisms to adjacent areas, manifesting divergent characteristics and intensities of impact across different economic and environmental spheres.

H3: *The digital economy exerts a spatial spillover effect on carbon dioxide emissions across different regions.*

3. Methods and data

3.1. Econometric model

In their seminal exploration of the determinants impacting the environment, Miller and Wilsdon (2001) postulated that environmental change is precipitated by a triad of factors: the demographic component, the affluence component, and the technological component. This conceptual framework, which they articulated, is encapsulated by the IPAT Equation, serving as a foundational model in the discourse of environmental science.

$$I = P * A * T. \tag{1}$$

In the original IPAT formulation, 'I' denotes environmental impact, 'P' represents demographic components, 'A' symbolizes economic growth (affluence factors), and 'T' indicates technological advancements. Building upon this foundation, Dietz and Rosa (1997) introduced the STIRPAT model – an analytical framework that examines the stochastic impacts of population, affluence, and technology on environmental pressure.

$$\frac{dI}{dt} = aPb^t At^T et^{\delta}. \tag{2}$$

In the Equation under consideration, the term '*a*' represents the intercept, while '*b*', '*c*', and '*d*' are the respective exponents correlating to the environmental impacts of *P* (population), *A* (affluence), and *T* (technology), with 'e_t' denoting a stochastic error component. Carbon emissions, a critical environmental metric, have been the focus of numerous academics (Ding et al., 2022) who have adopted and refined the STIRPAT model as a quantitative framework to examine the interplay between the digital economy and carbon emissions. Furthermore, acknowledging the influence of historical levels of carbon dioxide emissions, our model introduces a lagged variable of CO_2 emissions into the model, thereby effectively integrating the digital economy variable with the STIRPAT framework.

$$\begin{aligned} ceit &= \gamma 1 indust + \gamma 2 cei,t-1 + \gamma 3 digit + \gamma 4 pgdpit + \gamma 5 pgdpit^2 + \\ &\gamma 6 energyit + \gamma 7 fdit + \gamma 8 urbit + vi + ut + \varepsilon it. \end{aligned} \tag{3}$$

In the context of urban municipalities, denoted by *i*, across temporal spans denoted by *t*, the dependent variable carbon emissions is symbolized as *ce*. The term dig represents the digital economy, *pgdp* stands for economic growth, energy encapsulates the levels of energy consumption, fdi signifies foreign direct investment, and urb denotes the degree of urbanization. Herein, α_k, where k is an element of the set {1,7}, corresponds to the estimated coefficients. The variables v_i and u_t represent fixed effects that are specific to individual entities and temporal periods, respectively, while ε_{it} is the stochastic error term. To mitigate the issue of heteroscedasticity, we have employed a logarithmic transformation for all independent variables with the exception of the lagged variable of *ce* and *pgdp*. The retention of *pgdp* in its raw form is attributed to the inclusion of a squared *pgdp* term; thus, by taking the logarithm of only one variable, we attenuate the problem of multicollinearity. The same rationale applies to the lagged variable of *ce*.

To elucidate the potential mediating mechanisms through which the digital economy may influence carbon emission reduction, we have established a standardized mediation effect test model including models (3), (4) and (5). This model serves as an empirical tool to investigate whether industrial structure functions as a mediating variable in the relationship between the digital economy and carbon mitigation. The most widely adopted approach for testing mediation effects is the stepwise method introduced by Baron and Kenny (1986). We employ this methodology to examine the role of industrial structure as a potential mediator between the digital economy and carbon emission reduction. The specific formulation of our regression model is as follows:

$$\begin{aligned} industit &= \beta_0 + \beta_1 cei,t-1 + \beta_2 digit + \beta_3 pgdpit + \beta_4 pgdpit^2 + \\ &\beta_5 energyit + \beta_6 fdit + \beta_7 urbit + vi + ut + \varepsilon it; \end{aligned} \tag{4}$$

$$ceit = \alpha_0 + \alpha_1 cei,t-1 + \rho ceit + \phi_1 digi,t-1 + \alpha_2 digi + \phi_c Z_i,t + \alpha_c Z_i + ut + \varepsilon i,t. \tag{5}$$

The spatial spillover effects of the digital economy on carbon dioxide emissions, we integrate spatial interaction terms of these variables, along with other control variables, within models (3), (4), and (5). This extension advances our inquiry into a spatial panel econometric model, thereby enriching the analytical framework to better understand the underlying dynamics at play.

$$cei,t = \alpha_0 + \alpha_1 cei,t-1 + \rho Wcei,t + \phi_1 Wdigi,t + \alpha_2 digi + \phi_c Z_i,t + \alpha_c Z_i + ut + \varepsilon i,t; \tag{6}$$

$$indust,t = \beta_0 + \beta_1 cei,t-1 + \rho_W indust,t-1 + \phi_1 Wdigi,t + \beta_2 digi + \phi_c Z_i,t + \beta_c Z_i + ut + \varepsilon i,t; \tag{7}$$

$$cei,t = \gamma_0 + \gamma_1 indust + \rho_W indust,t + \gamma_2 cei,t-1 + \phi_1 Wdigi,t + \gamma_3 digi,t + \phi_c Z_i,t + \alpha_c Z_i + ut + \varepsilon i,t. \quad (8)$$

In the spatial Durbin models (6), (7) and (8), the symbol ρ denotes the spatial autoregressive coefficient, while W represents the matrix of spatial weights. Drawing from the methodology of Yi et al. (2022), this study employs an adjacency matrix W_{ij} to facilitate the regression analysis. The coefficients ϕ_1 and ϕ_c correspond to the elasticities associated with the core explanatory variables and the control variable spatial interaction terms, respectively. Equation (6) encompasses the spatial interaction terms for both the dependent and explanatory variables, thereby constituting a spatial Durbin model (SDM) with fixed effects over time.

$$W_{ij} = 1, i \text{ is adjacent to } j; 0, i \text{ is not adjacent to } j. \quad (9)$$

3.2. Variable selection

3.2.1. Dependent variable

This treatise adopts the carbon emission quantification predicated upon the methodologies delineated by Xin et al. (2023). The variable selected for computation is exclusively carbon dioxide (encompassing solely CO_2).

3.2.2. Key explanatory variable

The Digital Economy Index (dig) emerges as the pivotal explanatory variable within this study. Given the expansive nature of the digital economy – a concept that invariably encompasses a multitude of indices – the secondary and tertiary indicators employed by scholars frequently exhibit notable disparities. To address this, a comprehensive evaluation was undertaken, culminating in the adoption of the digital economy indicators as delineated by Xiao and Liu (2022). Moreover, in recognition of the foundational contribution of the postal sector to the infrastructure of the digital economy, an additional metric – the per capita postal index – was integrated to augment the digital economy indicators as shown in Table 1. The computation of these measures employed the entropy weighting method to ensure a robust and nuanced quantification.

Table 1. Measurement index system of the digital economy

	Primary indicators	Secondary indicators	Index attribute
Digital Economy Index	Internet penetration	The prevalence of internet users per hundred individuals	+
	Number of Internet-related workers	The proportion of professionals engaged in computer services and software-related occupations	+
	Internet-related outputs	Total telecommunication services per capita	+
	Number of mobile Internet users	Mobile phone subscribers per hundred individuals	+
	Digital finance inclusive development	China Digital Inclusive Finance Index	+
	Postal development	Per capita postal services	+

3.2.3. Intermediary variable

In this discourse, the ratio of the tertiary sector to the secondary sector is employed as a metric to gauge the industrial structure (indust).

3.2.4. Control variables

Wang et al. (2021) and Amoah et al. (2023) were among the precursors to unearth the intricate dynamics between economic development (pgdp, $pgdp^2$) and carbon emissions. Concomitantly, the economic expansion exerts an influence on carbon dioxide emissions that adheres to an Environmental Kuznets Curve (EKC) relationship. Thus, in the realm of control variables, we integrated the quadratic term of economic growth. Additionally, in contemplation of the enhancement in per capita income engendered by economic augmentation – which in turn stimulates consumption and influences carbon emissions – the decision was made to employ per capita GDP as the representative metric for economic growth.

Liu et al. (2022) employed panel data methodologies to investigate the intricate interplay amongst carbon dioxide emissions, urbanization, GDP, and energy consumption (energy) within a cohort of eleven nations from the Middle East and North Africa, they observed that an increased consumption of energy often correlates with a concomitant rise in carbon dioxide emissions. In accordance with the findings delineated by the Intergovernmental Panel on Climate Change (IPCC), the profligate combustion of fossil fuels and the consequent emissions of carbon dioxide stand as the principal culprits behind the phenomenon of global warming. According to the Li et al. (2021b) among the various fossil fuels, coal consumption represents a predominant share, henceforth, in the discourse of this manuscript, the term "energy consumption" shall be exemplified predominantly by the utilization of coal.

In the present discourse, we draw upon the methodological foundations established by Li et al. (2023b) adopting the ratio of actual foreign capital utilization to GDP as a metric to gauge the degree of economic openness. On the one hand, the liberalization of markets facilitates the ingress of foreign enterprises endowed with advanced emission-reduction technologies into China, catalyzing "pollution halo" effects that are conducive to carbon abatement. On the other hand, the inquiry by Scherbakov and Silkina (2019) posits that an augmentation in foreign direct investment is correlated with increased carbon dioxide emissions. In essence, whether as a catalyst for carbon emission reduction or as a contributor to increased emissions, FDI emerges as a significant variable likely to impact carbon output and, thus, merits inclusion as a control variable in our analysis. For the purposes of this study, the actual foreign investment to GDP ratio shall serve as the representative indicator of the level of openness indicated in Table 2.

The urbanization rate is defined by the proportion of the population residing within urban areas relative to the total permanent population at the prefecture level.

3.3. Data sources

Utilizing a comprehensive panel dataset encompassing 285 prefecture-level cities – excluding Hong Kong, Macau, and Taiwan – our analysis spans the period from 2011 to 2022. Research data were collected from National Bureau of Statistics of China (2024a), the State Statistics Bureau (China), China Statistical Yearbook (National Bureau of Statistics of China, 2024b), Chi-

Table 2. Variable description

Variable	symbol	name	Indictor
Dependent variable	ce	carbon emission	Natural logarithm of total carbon dioxide emissions
Key explanatory variable	dig	digital economy	Calculated according to the index system of the digital economy
Intermediary variable	Indust	industrial structure	Natural logarithm of the ratio of the tertiary sector to the secondary sector
Control variables	pgdp	per capita gdp	gdp divided by population of prefecture-level cities
	pgdp2	square of gdp per capita	Natural logarithm of gdp per capita squared
	energy	energy consumption	Natural logarithm of coal consumption
	fdi	Openness	Natural logarithm of the ratio of utilized foreign capital to GDP
	urb	urbanization rate	Natural logarithm of resident urban population over resident population in prefecture-level cities

na Energy Statistical Yearbook (National Bureau of Statistics of China, 2024c), EPS databases (EPS China Data, 2010–2023), Institute of Digital Finance Perking University (2021), China National Intellectual Property Administration (2022), National Bureau of Statistics of China (2024d) and Statistical yearbook of all provinces (autonomous regions, municipalities). The missing values are supplemented by interpolation. The statistical analysis software used in this paper is Stata 17.0.

4. Empirical results and discussion

4.1. Descriptive statistics

The Table 3 presents summary statistics for a dataset comprising 3.065 observations across various variables. The variable ce (carbon emissions) has a mean of 10.053 with a standard deviation of 0.947, ranging from a minimum of 7.487 to a maximum of 13.56, indicating relatively moderate variation in carbon emissions across the dataset. The indust variable, representing industrial activity, shows a mean of 0.133 with a standard deviation of 0.563, and values ranging from –1.175 to 2.643, reflecting a broad range of industrial activity levels, including some negative values, which may indicate declines in certain areas. The dig variable, which likely represents digital economy metrics, has a mean of –1.48 with a standard deviation of 0.684, and ranges from –3.582 to 1.801, suggesting that most observations are on the negative side, possibly indicating a generally lower level of digital economy development or adoption. The co22 variable, representing CO_2 emissions, has a mean of 6,036 units with a significant standard deviation of 5,985, and a wide range from 1,650.4 to 112,743, highlighting substantial variability in emissions across different observations. The pgdp variable, reflecting per capita GDP, shows a mean of 72,167 with a standard deviation of 23,699, and values ranging from 16,457 to 567,749, indicating considerable economic disparity within the dataset. The square of per capita GDP (pgdp2) has a mean of 24.38 and a standard deviation of 2.151, with values between 19.55 and 29.11, reflecting the quadratic nature of the relationship captured by this variable. Energy consumption (energy) has a mean of 6.473 with a standard deviation of 1.679, ranging from 2.384 to 10.347, indicating some variability in energy use across observations. The FDI variable, representing foreign direct investment, has a mean of –3.048 with a higher standard deviation of 3.696, and ranges from –13.03 to 1.553, showing significant variation in FDI inflows, with many observations possibly indicating net outflows. Finally, the urb variable, representing urbanization, has a mean of 4.179 with a standard deviation of 0.366, and values ranging from 3.563 to 5.605, suggesting moderate variability in urbanization levels within the dataset. Overall, the table provides a comprehensive overview of the central tendencies and variabilities of key variables in the study, highlighting both economic and environmental aspects.

Table 3. Descriptive statistics

Variable	Obs	Mean	SD	Min	Max
ce	3,065	10.053	0.947	7.487	13.56
indust	3,029	0.133	0.563	–1.175	2.643
dig	3,065	–1.48	0.684	–3.582	1.801
co22	3,065	6036	5985	1650.4	112743
pgdp	3,065	72167	23699	16457	567749
pgdp2	3,065	24.38	2.151	19.55	29.11
energy	3,065	6.473	1.679	2.384	10.347
fdi	3,065	–3.048	3.696	–13.03	1.553
urb	3,065	4.179	0.366	3.563	5.605

4.2. Spatial correlation test results

In this study, we rigorously evaluated spatial dependence in accordance with the methodology delineated by Xue et al. (2022) subsequently selecting the most appropriate spatial econometric model to encapsulate the observed phenomena. Our initial investigative step entailed the application of Moran's I statistic to assess the presence of spatial autocorrelation amongst observations within the context of a geographically weighted adjacency matrix. We systematically employed LM tests for both lag and error to ascertain the existence of spatially lagged dependent variables as well as spatially autocorrelated error term, respectively, then to thereby select an appropriate spatial model. Finally we choose the Spatial Durbin Model according to the LM results). Furthermore, LR tests were utilized to determine whether the Spatial Durbin Model (SDM) could conceivably degenerate into either a Spatial Autoregressive (SAR) or a Spatial Error Model (SEM), following the insights provided by Xue et al. (2022).

An examination of Table 4 reveals that, between the years 2011 and 2022, the Moran's I values are modest, the associated p-values are all less than 0.05, indicating statistical significance at the 0.05 level. Consequently, we infer the presence of spatial autocorrelation.

Table 4. Moran's I values of carbon emission

Year	Variable	I	E(I)	sd(I)	z	p-value*
2011	C2011	0.105	–0.004	0.053	2.758	0.009
2012	C2012	0.104	–0.004	0.053	2.732	0.012
2013	C2013	0.105	–0.004	0.054	2.741	0.011
2014	C2014	0.105	–0.004	0.053	2.762	0.009
2015	C2015	0.105	–0.004	0.053	2.744	0.011
2016	C2016	0.107	–0.004	0.054	2.801	0.006
2017	C2017	0.108	–0.004	0.054	2.841	0.003
2018	C2018	0.103	–0.004	0.053	2.695	0.015
2019	C2019	0.104	–0.004	0.054	2.706	0.014
2020	C2020	0.109	–0.004	0.055	2.861	0.002
2021	C2021	0.11	–0.004	0.055	2.901	0.0016
2022	C2022	0.111	–0.004	0.055	2.941	0.0012

4.3. Baseline regression results

This study principally employs a temporally invariant spatial panel Durbin model for regression analysis. In acknowledgment of potential endogeneity, and to facilitate comparative analysis, Table 5 enumerates the regression outcomes derived from employing an array of econometric methodologies, including Ordinary Least Squares (OLS), Random Effects Model, Fixed Effects Model, and the Generalized Method of Moments (GMM) dynamic panel model.

Analysis of the data presented in Table 5 reveals that the coefficient relating the level of digital economic development to carbon emission intensity is consistently positive across all above five models, indicating that the advancement of the digital economy correlates with an increase in carbon emission intensity. This observation substantiates Hypothesis 1. Furthermore, results from the Spatial Durbin Model (SDM) in column (5) of Table 5 demonstrate that the coefficient for the spatial lag of digital economic development is significantly positive at the 1% level. Moreover, the coefficient of the spatial lag term for the level of digital economic development, as presented in column (5) of Table 5, is statistically significant and positive at the 1% level.

Comparing these results with similar studies, Umair and Dilanchiev (2022) and Zhang and Umair (2023) also found a positive relationship between digital economic development and carbon emissions, supporting the findings of this study. Both studies emphasized the importance of energy consumption and industrial structure in mediating this relationship. On the other hand, studies by Li and Umair (2023b) and Xiuzhen et al. (2022) highlighted the spatial spillover effects of carbon emissions, aligning with the findings of the SDM models in this study, which show significant spatial dependence.

The data from 2012 to 2022 provides a detailed comparison of carbon dioxide (CO_2) emissions and emission intensity between digital manufacturing and service industries in different regions. The Figure 1 display two sets of data. The left y-axis represents the total CO_2 emissions in megatons (Mt), shown by the bars. The right y-axis represents the emission intensity in tonnes per million USD, depicted by the line plots with markers. Graph (a) illustrates the

Table 5. Baseline regression results

Model	(1) ols	(2) re	(3) fe	(4) sys-gmm	(5) sdm
Variable	ce	ce	ce	ce	ce
dig	0.518488***	0.368180***	0.412939***	0.620054***	0.515616***
	–0.04146	–0.03874	–0.03902	–0.0511	–0.05517
l.ce	0.007475***	0.004278***	0.003968*	0.006457***	0.005453***
	–1.9E-05	–1.9E-05	–2.7E-05	–8E-06	–7E-06
pgdp	–0.012100**	–0.008800**	–0.006600*	–0.013200***	–0.011200**
	–0.0008	–0.0002	–0.0002	–0.0003	–0.0004
pgdp2	–0.919809**	–0.984011**	–1.001808**	–1.131744***	–1.041105**
	–0.21491	–0.10681	–0.10623	–0.16137	–0.1583
energy	0.435035**	0.395421***	0.394798***	0.611108***	0.301571
	–0.10457	–0.06117	–0.06141	–0.13445	–0.07609
fdi	0.391691***	0.234176*	0.245110**	0.394159***	0.257481***
	–0.08753	–0.04445	–0.04274	–0.0898	–0.10273
urb	0.201772	0.400571*	0.452041*	0.348249***	0.410668
	–0.09339	–0.08553	–0.08443	–0.12866	–0.09174
_cons	9.820006***	8.582692***	8.713432***	10.842162***	
	–0.50878	–0.29449	–0.31198	–0.36945	
Wx					
dig					0.614690***
					–0.07171
l.ce					0.500109***
					–0.00417
pgdp					0.860061***
					–0.005
pgdp2					–1.360680**
					–0.65952
energy					0.655504
					–0.21309
fdi					–0.423874**
					–0.10591
urb					0.896831
					–0.27294
Spatial					
rho					0.786064
					(.)
Variance					
sigma2_e					0.129435***
					–0.50821
AR (1)				Pr > z = 0.000	
AR (2)				Pr > z = 0.291	
Hansen test				Prob > chi2 = 0.103	

Note: Standard errors in parentheses *p < 0.1, **p < 0.05, ***p < 0.01.

digital manufacturing industry and indicates regional variations in CO_2 emissions and emission intensity. Certain regions exhibit increased CO_2 emissions during five years, whereas others demonstrate a decrease. The emission intensity in the digital manufacturing industry shows a consistent pattern, indicating a possible correlation between emission volumes and intensity. In contrast, the digital service industry in Graph (b) shows more significant variability between 2012 and 2017 than the manufacturing sector. Nevertheless, the emission intensity of the service industry exhibits a distinct dynamic, where the correlation between total emissions and emission intensity may not be as direct as observed in the manufacturing sector. Presenting both absolute emissions and intensity offers a more nuanced comprehension of the environmental impact of these industries, considering their overall contribution to CO_2 emissions and their efficiency in their economic output. An in-depth analysis of this nature is becoming progressively crucial for policymakers and stakeholders who promote sustainable industry expansion while mitigating carbon emissions.

The Figure 2 comparing economic dynamics between regions in 2012 and 2022 show four sections: multipliers, spillovers, feedback and spillovers. These indicate how we view the economic benefits and impacts within and between regions. Each chart shows the economic

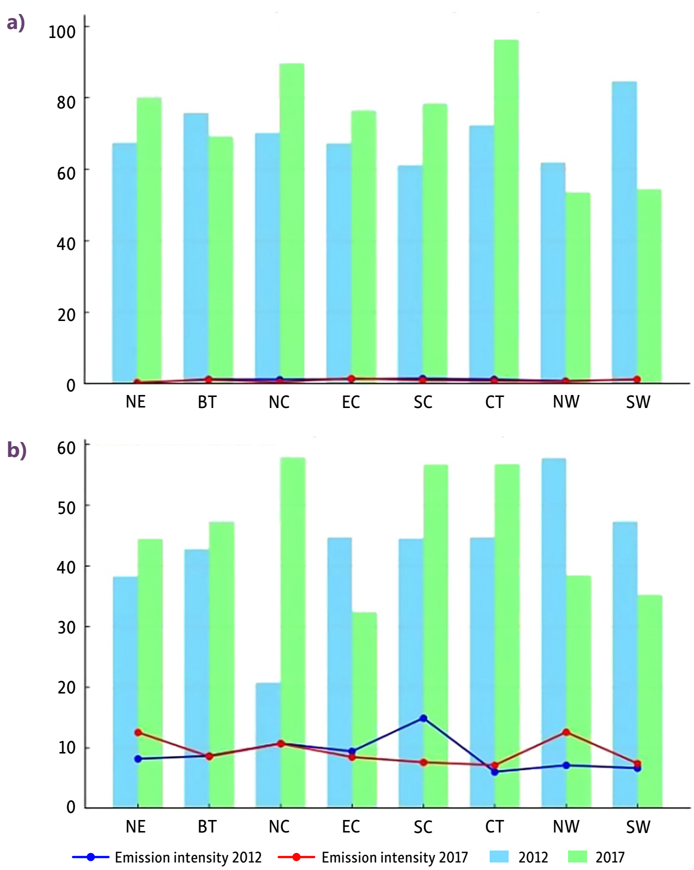

Figure 1. Implicit carbon emissions from digital industries:
a – digital manufacturing industry; b – digital service industry

interactions during the five years. In some regions, intra-regional multipliers dominate, meaning that economic activities within the region self-stimulate the economy of that region – and in the other areas, inter-regional multipliers dominate, meaning that those regions' economies affect or are injected into the economies of others. Intra- and inter-regional dynamics

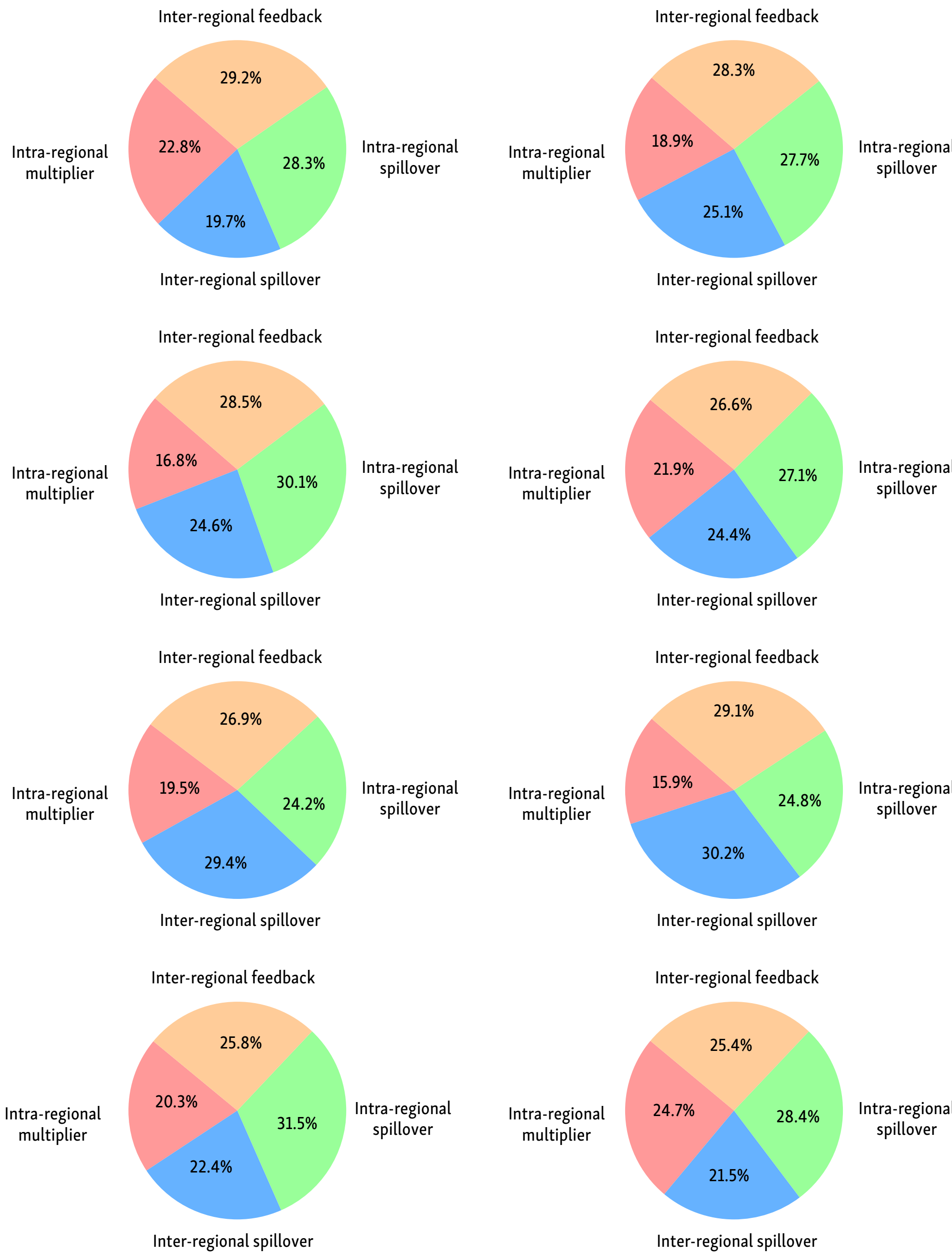

Figure 2. Decomposition of carbon emission pathways for digital industries

shifted economic patterns in several regions from 2012 to 2022. The NE region showed that intra-regional multipliers decreased and inter-regional feedback multipliers increased. This reflects that the region's economy has become more influenced and possibly dependent on external regional economies. Understanding such dynamics can help regional planners and policymakers design strategies to bolster regional economies while being mindful of their connectivity.

4.4. Mediating effect analysis

This section empirically examines Hypothesis 2, which postulates the mediating role of industrial structure in the relationship between the digital economy and carbon emissions. The examination adheres to the established procedural framework of mediation effect models. Our study employs the widely acclaimed stepwise approach suggested by Wang et al. (2022) and Wu et al. (2023) for mediation effect analysis. Furthermore, for the purposes of comparative analysis and robustness assessment, we present the estimation outcomes of several econometric models including the Ordinary Least Squares (OLS) model, Random Effects model, Fixed Effects model, the Generalized Method of Moments (GMM) dynamic panel model, and the Durbin model, all of which are delineated in Table 6. The coefficient for the variable dig (digital economy) is consistently positive and highly significant across all models, with values ranging from 0.5188 in OLS (1) to 1.1585 in OLS (2) and 0.9292 in SDM (14), indicating a strong positive impact of the digital economy on carbon emissions (CE). This suggests that the digital economy is a significant driver of carbon emissions, both directly and indirectly through its influence on industrial structures. The lagged carbon emissions variable (l.ce) also shows positive and significant coefficients across all models, with values such as 0.07475 in OLS (1) and 0.06457 in GMM (10), indicating that past carbon emissions have a persistent effect on current emissions, reflecting temporal dependence. The PGDP variable, representing per capita GDP, generally has a negative and significant impact on carbon emissions in most models, such as –0.0021 in OLS (1) and –0.0012 in SDM (15). However, in models where PGDP is squared (pgdp2), the coefficients are significantly negative, such as –1.192 in OLS (1) and –2.3132 in GMM (11), supporting the Environmental Kuznets Curve (EKC) hypothesis, where carbon emissions initially rise with economic growth but eventually decrease as economies develop further. The energy variable is positive and significant in most models, particularly in OLS (1) at 0.4335 and SDM (13) at 0.7519, indicating that higher energy consumption is associated with increased carbon emissions. This relationship underscores the energy-intensive nature of economic activities contributing to higher emissions. Foreign direct investment (FDI) has mixed effects, with generally positive and significant coefficients, such as 0.5192 in OLS (1) and 0.3154 in SDM (15), suggesting that FDI inflows tend to increase carbon emissions, potentially due to the transfer of energy-intensive industries. However, negative effects are observed in some models, indicating that under certain conditions, FDI may contribute to emission reductions. The urbanization variable (urb) shows a positive but varying impact on carbon emissions, with coefficients such as 0.5072 in OLS (1) and 1.9559 in GMM (11), suggesting that urbanization contributes to increased carbon emissions, likely due to higher energy consumption and industrial activities in urban areas. The industrial structure (indust) is consistently positive and significant in models where it is included, with coefficients like 0.2803 in OLS (2) and 0.2560 in SDM (15), indicating that changes in industrial structures towards more energy-intensive activities contribute to higher carbon emissions. Overall, the results from this table underscore the complex interplay between economic development, industrial structures, and carbon emissions. The digital economy and energy consumption are key drivers of emissions, while economic growth, as captured by PGDP and PGDP2, follows the EKC hypothesis, where emissions eventually decline after reaching a certain level of development. The mixed impact of FDI and urbanization further highlights the nuanced effects of globalization and urban growth on environmental outcomes.

Table 6. Mediating effect testing results

Model Type	OLS (1)	OLS (2)	OLS (3)	RE (4)	RE (5)	RE (6)	FE (7)	FE (8)	FE (9)	GMM (10)	GMM (11)	GMM (12)	SDM (13)	SDM (14)	SDM (15)
Variable	CE	Indust	CE	CE	Indust	CE	CE	Indust	CE	CE	Indust	CE	CE	Indust	CE
dig	0.5188***	1.1585***	0.6472***	0.5178***	1.0286***	0.5758***	0.6273***	0.9552***	0.5831***	0.7220***	0.9303***	0.7025***	0.6016***	0.9292***	0.5626***
	–0.0515	–0.0658	–0.0673	–0.0316	–0.0461	–0.0339	–0.0309	–0.0642	–0.0328	–0.0331	–0.1488	–0.0424	–0.0452	–0.0511	–0.0471
l.ce	0.07475***	0.05082***	0.06467***	0.05278***	0.0402***	0.0458***	0.0568***	0.0574***	0.0542***	0.06457***	0.05031***	0.06442***	0.06453***	0.0579***	0.06448***
	–0.002	–0.002	–0.0019	–0.0025	–0.0029	–0.0021	–0.0017	–0.0029	–0.0015	–0.0008	–0.0062	–0.0013	–0.0007	–0.0009	–0.0007
pgdp	–0.0021***	0.0222**	–0.0021***	–0.0008***	–0.0050***	–0.0008***	–0.0006**	–0.0020***	–0.0006**	–0.0032***	0.0270***	–0.0044***	–0.0012***	0.0290***	–0.0014***
	–0.0008	–0.0009	–0.0008	–0.0003	–0.0005	–0.0003	–0.0003	–0.0007	–0.0003	–0.0003	–0.0067	–0.0004	–0.0004	–0.0005	–0.0004
pgdp2	–1.192***	–2.061***	–1.034***	–0.984***	–1.932***	–1.046***	–1.302***	–2.033***	–1.094***	–1.133**	–2.3132**	–1.103**	–1.2410***	–2.3005***	–1.2604***
	–0.215	–0.26	–0.225	–0.203	–0.312	–0.205	–0.215	–0.38	–0.215	–0.161	–0.294	–0.241	–0.158	–0.196	–0.165
energy	0.4335***	0.4053	0.4911***	0.4295***	0.4217	0.4480***	0.4295***	0.5405**	0.4275***	0.6761***	0.8849**	0.7519***	0.5032	0.6376***	0.5019
	–0.105	–0.105	–0.102	–0.069	–0.191	–0.067	–0.068	–0.232	–0.065	–0.134	–1.793	–0.242	–0.076	–0.094	–0.076
fdi	0.5192***	0.1041	0.4122***	0.1034**	–0.0192**	0.3019***	0.2955***	–0.1220***	0.3025**	0.4194***	0.0601***	0.3121***	0.3157***	0.2113***	0.3154***
	–0.039	–0.053	–0.042	–0.015	–0.078	–0.014	–0.015	–0.076	–0.014	–0.019	–0.232	–0.031	–0.024	–0.029	–0.024
urb	0.5072	1.066***	0.8727**	0.5901*	1.5878***	0.5424	0.6902*	1.4394***	0.5395	0.4952***	1.9559**	0.8344***	0.6311	1.0637	0.6413
	–0.093	–0.147	–0.148	–0.151	–0.16	–0.153	–0.152	–0.162	–0.151	–0.186	–1.592	–0.209	–0.142	–0.152	–0.143
indust		0.2803***			0.2766***			0.2816***			0.2479**			0.2560***	
		–0.123			–0.133			–0.139			–0.141			–0.141	
_cons	10.2902***	9.3649***	9.0018***	8.1583***	9.8568***	9.9056***	8.2134***	7.3139**	9.9430***	10.2342***	10.0024	11.5414***			
	–0.44	–0.521	–0.467	–0.243	–0.762	–0.239	–0.241	–0.96	–0.224	–0.27	–5.223	–0.44			

Note: Standard errors in parentheses *p < 0.1, **p < 0.05, ***p < 0.01.

As illustrated in the accompanying figure, the regression results from the five models – ordinary least squares (OLS), random effects (RE), generalized method of moments (GMM), and spatial Durbin model (SDM) – all corroborate the intermediary role of industrial structure in the nexus between digital economy and carbon emissions. In our analysis, predicated on the models (6), (7), and (8). We primarily investigate the mediating effect of industrial structure within the framework of the SDM model.

The robustness test results presented in Table 7 indicate the stability and consistency of the key findings across various econometric models, including OLS, RE, FE, GMM, and SDM. The variable dig (digital economy) consistently shows a positive and highly significant impact on carbon emissions (ce) across all models, with coefficients ranging from 0.3758 in OLS (3) to 0.6220 in RE (6). This suggests that the positive relationship between the digital economy and carbon emissions is robust, irrespective of the model specification used, reinforcing the conclusion that digital economic activities are a significant driver of emissions. The lagged carbon emissions variable (l.ce) also remains consistently positive and significant, with coefficients such as 0.07475 in OLS (1) and 0.08457 in GMM (10), indicating that past emissions have a persistent and significant impact on current emissions levels. This temporal dependence highlights the ongoing effect of historical emissions on current environmental outcomes.

The variable PGDP (per capita GDP) shows mixed effects across different models. While the coefficients are generally negative and significant in many cases, such as –0.0021 in OLS (1) and –0.0008 in RE (4), the presence of positive and significant coefficients in models like OLS (2) at 0.0222 suggests a nuanced relationship between economic growth and emissions. The squared term pgdp2 consistently displays negative and significant coefficients, such as –1.192 in OLS (1) and –2.3132 in GMM (11), supporting the Environmental Kuznets Curve (EKC) hypothesis, which posits that emissions initially increase with economic growth but eventually decline as economies mature. Overall, the robustness test confirms the reliability of the initial findings. The digital economy's role in driving emissions, the temporal persistence of emissions, and the EKC hypothesis remain robust across various model specifications. These results underscore the importance of considering the digital economy and economic growth stages in understanding and managing carbon emissions.

Comparing these results with similar studies, Cheng et al. (2023) and Li et al. (2021a) also found a positive relationship between digital economic development and carbon emissions, supporting the findings of this study. Both studies emphasized the importance of energy consumption and industrial structure in mediating this relationship (Yang et al., 2022). On the other hand, studies by Zhang et al. (2022) highlighted the spatial spillover effects of carbon emissions, aligning with the findings of the SDM models in this study, which show significant spatial dependence.

Table 7. Robustness test

Variable	OLS (1)	OLS (2)	OLS (3)	RE (4)	RE (5)	RE (6)	FE (7)	FE (8)	FE (9)	GMM (10)	GMM (11)	GMM (12)	SDM (13)	SDM (14)	SDM (15)
ce	ce	ce	ce	ce	ce	ce	ce	ce	ce	ce	ce	ce	ce	ce	ce
Main															
dig	0.5188***	0.4472***	0.3758***	0.5178***	0.4831***	0.6220***	0.5016***	0.4626***							
	–0.0515	–0.0573	–0.0439	–0.0416	–0.0428	–0.0431	–0.0525	–0.0571							
l.ce	0.07475***	0.0582***	0.0667***	0.07278***	0.0702***	0.0758***	0.0768***	0.0774***	0.0742***	0.08457***	0.06031***	0.08442***	0.08453***	0.0679***	0.08448***
	–0.002	–0.002	–0.0019	–0.0025	–0.0029	–0.0021	–0.0017	–0.0029	–0.0015	–0.0008	–0.0062	–0.0013	–0.0007	–0.0009	–0.0007
pgdp	–0.0021***	0.0222**	–0.0021***	–0.0008***	–0.0050***	–0.0008***	–0.0006**	–0.0020***	–0.0006**	–0.0032***	0.0270***	–0.0044***	–0.0012***	0.0290***	–0.0014***
	–0.0008	–0.0009	–0.0008	–0.0003	–0.0005	–0.0003	–0.0003	–0.0007	–0.0003	–0.0003	–0.0067	–0.0004	–0.0004	–0.0005	–0.0004
pgdp2	–1.192***	–2.061***	–1.034***	–0.984***	–1.932***	–1.046***	–1.302***	–2.033***	–1.094***	–1.133**	–2.3132**	–1.103**	–1.2410***	–2.3005***	–1.2604***
	–0.215	–0.26	–0.225	–0.203	–0.312	–0.205	–0.215	–0.38	–0.215	–0.161	–0.294	–0.241	–0.158		

5. Conclusions and policy implications

5.1. Conclusions

This study, drawing on a panel dataset of Chinese prefecture-level cities from 2011 to 2022, constructs a Digital Economy Development Index and employs a suite of econometric models, including a Dynamic Spatial Durbin Model with time-fixed effects, System GMM, and mediation effect models (utilizing the three-step procedure and the bootstrap method). It rigorously examines the carbon emission reduction mechanisms and the efficacy of the digital economy from multiple dimensions. The key findings are as follows: Firstly, the digital economy has notably augmented carbon emissions. Upon conducting a series of endogeneity tests and robustness tests, the conclusion remains intact. At the same time, the digital economy possesses a significant spatial spillover effect. Secondly, carbon emissions demonstrate a pronounced spatiotemporal dependency effect. Temporally, emissions exhibit a marked "snowball" effect; should the level of carbon emissions be elevated in one period, it is likely to ascend in the subsequent period. Spatially, previous emissions levels also display a distinct spatial spillover effect. Thirdly, the digital economy exerts influence on carbon emissions through both direct and indirect mechanisms. It can directly augment carbon emissions, and it can also indirectly augment carbon emissions by altering the industrial framework (increasing the ratio of the tertiary sector relative to the secondary sector). The evaluative metrics for assessing the level of digital economic development are not sufficiently comprehensive, resulting in a lack of precision in the outcome measurements. Constructing a more robust framework of indicators for the digital economy's level of development would be advantageous for future inquiries. Moreover, as new datasets become available, it is conceivable to expand the temporal scope of panel data, thereby facilitating more profound research. For instance, by broadening the temporal dataset, one could undertake non-linear analyses to evaluate whether the impact of the digital economy on carbon emissions follows an inverted U-shaped curve. This would allow for a more nuanced exploration of whether the digital economy might engender a carbon reduction effect in its future trajectory.

5.2. The policy implications

Firstly, in light of the "snowballing" impact of carbon emissions within China, the attainment of peak carbon emissions and carbon neutrality necessitates the establishment of enduring mechanisms. These mechanisms must ensure the coherence and sustainability of emission reduction policies, fostering a harmonious and coordinated implementation of carbon reduction strategies across various regions.

Secondly, the proliferation of the digital economy is poised to markedly escalate carbon emissions within China, exerting a spatial spillover effect. In this context, it is incumbent upon the government to concurrently foster the growth of the digital economy and remain vigilant of its environmental ramifications. There may be a requisite need to devise and enact more stringent carbon emission standards to ensure that the expansion of the digital economy does not proceed at the expense of environmental integrity. Moreover, regional governments ought to fortify policy coordination, collaboratively establishing and implementing measures to curtail carbon emissions. For instance, the establishment of regional carbon trading markets could be instrumental in facilitating the equitable distribution and allocation of emission rights. Simultaneously, the enhancement of inter-regional carbon emission monitoring is critical to ascertain that the carbon emission levels are effectively regulated amidst the development of the digital economy. This could be achieved through the establishment of a unified carbon monitoring framework and a data-sharing platform to foster technical exchange and collaboration amongst regions, jointly researching and promulgating low-carbon technologies to mitigate the digital economy's carbon footprint. Furthermore, during the planning and implementation phases of digital economy initiatives, there should be a heightened emphasis on assessing the projects' environmental impact to ensure that the execution does not detrimentally affect the environmental conditions of other regions.

Thirdly, the digital economy has the potential to escalate carbon emissions through the transformation of industrial frameworks, notably by augmenting the proportion of the tertiary sector. It behooves governmental entities to implement pertinent environmental stratagems, such as the institution of carbon taxation and the establishment of carbon emissions trading schemes, employing economic mechanisms to incentivize the tertiary sector to curtail its carbon footprint. Concurrently, there should be a strategic optimization of the industrial composition, with a vigilant eye on the carbon emissions that may arise amid the adjustment process. For instance, within the tertiary sector, there should be an encouragement of the growth of industries that are characterized by low carbon or carbon-neutral profiles. Alternatively, the promotion of technological innovation and the refinement of operational processes can enhance the energy efficiency within the sector, thereby diminishing the carbon emissions per unit of economic output.

In conclusion, the formulation of policy must contemplate the establishment of enduring frameworks to achieve the zenith of carbon emissions and carbon neutrality. Concurrently, as we champion the advancement of the digital economy, it is imperative to maintain a vigilant regard for the environmental ramifications, enacting stringent standards for carbon emissions. Moreover, the optimization of industrial configurations is essential, with a particular impetus on the encouragement of low-carbon or carbon-neutral sectors within the tertiary industry.

Disclosure statement

The authors declare no conflict of interest.

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