CAN THE MARKET-ORIENTED ALLOCATION OF DATA FACTORS PROMOTE URBAN POLLUTION AND CARBON REDUCTION? EVIDENCE FROM CHINA

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Abstract. In the digital-economy era, the market-oriented allocation of data factors as a new production-factor allocation mechanism not only lays a foundation for exploiting the multiplier effect of data factors but also provides fresh impetus for accelerating the economy's green economic transformation. Using panel data for 269 Chinese cities from 2010 to 2022 and treating the establishment of data trading platform as a quasi-natural experiment, this study employs a multi-period DID model to examine the influence of the market-oriented allocation of data factors on urban pollutant and carbon emissions. The results show, first, that the market-oriented allocation of data factors significantly suppresses urban pollutant emissions and carbon emissions, with the effect intensifying over time; second, that energy-structure optimization, technological innovation, and industrial-structure upgrading constitute the main channels through which the market-oriented allocation of data factors achieves pollution and carbon reduction; third, that the pollution reduction and carbon reduction effect is more pronounced in regions characterized by high data-processing efficiency, agglomeration of digital talent, and advanced digital technologies; and fourth, that the free flow of data factors both raises the overall level of green economic development and strengthens the market's primary allocative role, thereby reducing distortions in capital and labor and alleviating resource misallocation. These findings provide a new theoretical perspective on the environmental regulatory function of the market-oriented allocation of data factors and offer empirical support for institutional innovations that promote deep integration of the digital economy and green development.
Keywords: *circulation of data factors, common origin of carbon and pollutants, energy-efficiency improvement, green technological innovation, industrial-structure upgrading*

Introduction

As an active participant in global climate governance, China announced its "dual-carbon" strategy at the 2020 United Nations conference, pledging to achieve carbon peaking by 2030 and carbon neutrality by 2060. The Report to the 20th National Congress of the Communist Party of China explicitly called for "advancing pollution reduction and carbon reduction, expanding environmental capacity, and fostering green growth through the coordinated promotion of ecological conservation, resource conservation, and low-carbon development." This mandate signals that China's environmental governance system is undergoing a systemic transformation from single-pollutant control to an integrated approach emphasizing the synergies of pollution reduction and carbon reduction. Both atmospheric pollutants and greenhouse gas emissions originate primarily from fossil fuel combustion, sharing common sources, drivers, and processes. Recognizing this convergence allows policymakers to achieve simultaneous environmental and climate benefits through targeted interventions and innovative mechanisms. Coordinating pollution reduction and carbon reduction is therefore a crucial pathway for realizing an economy-wide green transition under the new development paradigm. The *2023 Urban Energy Transition White Paper* reports that energy-related

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carbon emissions from cities now account for 71%-76% of global totals. Concurrently, the *2023 Bulletin on China's Ecological and Environmental Status* issued by the Ministry of Ecology and Environment indicates that, among 339 prefecture-level and higher-level cities nationwide, 136 exceeded ambient-air-quality standards. These findings underscore that cities are both the principal loci of environmental pollution and carbon emissions and the primary areas in which pollution reduction and carbon reduction synergies must be realized.

In the current era, in which the digital-economy paradigm is profoundly restructuring the global system for allocating productive resources, the market-oriented allocation of data factors has become a crucial mechanism driving urban air-pollutant control and the reduction of city-level carbon emissions. By treating data as a factor of production to be allocated and utilized through market forces, the market-oriented allocation of data factors enables the efficient use of data throughout collection, storage, processing, and analysis. The introduction of market mechanisms and the resulting improvements in data-use efficiency allow governments and enterprises to devise and implement more scientific environmental policies and emission-reduction measures on the basis of precise data analytics (Zhao et al., 2024). The broad application of data also fosters intelligent decision-making and precise governance, making the monitoring and management of regional pollution sources more effective and thereby reducing emissions at their origin. Accordingly, a thorough examination of the role of the market-oriented allocation of data factors in synergistic pollution reduction and carbon reduction has become a critical topic in contemporary green-development research. Environmental-Kuznets-Curve (EKC) theory holds that economic development affects environmental quality through scale, technology, and structural effects. As the economy advances to higher stages, the pollution-mitigation impacts of technological progress and structural adjustment can offset the adverse scale effect. Realizing these technology- and structure-based environmental benefits is therefore indispensable for reconciling economic growth with environmental protection. Because enterprises are major sources of pollution and carbon emissions, determining how firms can reduce emissions is equally urgent. Against this backdrop, it is essential to ask whether data factors, as a new productive input, can generate technology and structural effects that yield pollution reduction and carbon reduction; whether, owing to their virtual, rapid circulation and novel production-factor attributes, the environmental benefits of data factors can further promote regional synergy between environmental protection and economic growth; and whether they can alleviate factor distortions, correct resource misallocation, and reduce waste. Regrettably, few scholars have explored the environmental attributes of data factors, and related studies remain scarce. This study treats the establishment of data trading platform as a quasi-natural experiment and employs a multi-period difference-in-differences model to investigate these questions.

Review of literature

Existing studies furnish critical empirical insights into the ecological and environmental consequences of the digital economy. Current scholarly discourse on data factors proceeds along two principal trajectories. First, regarding the participation of data factors in production, data, like land and capital, can become an actual factor of production only when combined with other inputs or resources (Xie et al., 2020). Evidence shows that the factor bundle formed by integrating data factors with human capital can effectively spur corporate innovation (Tao and Ding, 2022). Yet other studies identify a potential “data-factor trap”: large firms richly endowed with data resources tend to pursue incremental rather than breakthrough innovation, whereas resource-constrained small and medium-sized enterprises face low success probabilities in carrying out breakthrough projects (Xu et al., 2023). These dynamic limits any substantial rise in aggregate innovation. Second, considering the intrinsic properties of data factors, their high diffusivity and strong permeability foster a qualitative shift in growth drivers and accelerate the transition from an industrial economy to a digital economy (Song et al., 2023). Data factors direct labor, capital, and other traditional inputs toward enterprises or sectors with superior data-use efficiency, enabling the rational allocation of production factors and advancing industrial digitalization (Zhu et al., 2024). Although data-enabled industrial digitalization can raise productivity and expand real output, the digital industry itself is energy-intensive, which may lead to an unintended “green paradox” (Shi, 2022). Nevertheless, existing evidence indicates that, relative to the carbon-intensive tendency of digital industrialization, a larger scale of industrial digitalization yields a stronger carbon-mitigation effect. When industrial digitalization is high and digital industrialization is low, the digital economy exhibits a significant impact on pollution reduction and carbon reduction (Yang et al., 2023). Accordingly, the “green paradox” associated with the digital industry should be regarded as a weak paradox, implying that over the long term the sector becomes environmentally friendly. At the macro level, prior research demonstrates that the short-term agglomeration of data factors widens regional development gaps, whereas over the long term it narrows these disparities, promotes coordinated regional development, and supports the attainment of common prosperity (Su, 2022).

In summary, the existing literature has investigated the economic effects of data factors from multiple angles, yet it rarely considers their environmental effects, and no consensus has emerged on how to measure data factors. Data factors generate immediate value through actor networks, digital infrastructure, and institutional arrangements, and the establishment of data trading platforms further reinforce these three foundations. Accordingly, this study regards the establishment of data trading platform as a quasi-natural experiment and employs a multi-period difference-in-differences (DID) model to examine the pollution reduction and carbon reduction effect of the market-oriented allocation of data factors. The marginal contributions of this paper are as follows. First, it expands the research frontier of the market-oriented allocation of data factors from the perspective of resources and the environment. Whereas prior studies emphasize economic outcomes, this paper systematically explores environmental effects, offering new insights for modern environmental governance. Second, existing studies usually measure data factors by counting keyword frequencies in corporate reports or constructing composite indices, approaches that are susceptible to measurement error and endogeneity. By using a multi-period DID framework, this paper more accurately identifies the pollution reduction and carbon reduction effect of the market-oriented allocation of data factors. Third, within the EKC framework, the paper clarifies three potential pathways through which the market-oriented allocation of data factors influences pollutant and carbon emissions, namely energy-mix optimization, technological progress, and industrial-structure upgrading. Empirical evidence then pinpoints the operative pathways, providing a basis for fully leveraging the pollution reduction and carbon reduction potential of the market-oriented allocation of data factors.

Theoretical analysis and research hypotheses

Policy background

Data factors constitute a critical driver of innovation in the digital era and serve as a key source for the innovative allocation of other resources. Unlike traditional inputs, data factors possess strong enabling power as a new type of production factor; they have progressively integrated into production, distribution, circulation, and consumption, thereby maximizing incremental value creation. Beginning in 2014, regions across China initiated exploratory practices in the establishment of data trading platform (as shown in *Table 1*). These platforms are intended to facilitate the circulation of data factors and to activate their market value, thereby promoting the deep integration of big data with the real economy, amplifying the complementary and multiplicative effects of data on traditional production factors, optimizing the regional allocation of resources, and advancing high-quality economic and social development.

Table 1. *First batch of data trading institutions in Chinese cities*

Name	Established time	City	Name	Established time	City
Zhongguancun ShuHai Big Data Trading Platform	2014	Beijing	Jilin Northeast Asia Big Data Service Center	2018	Changchun
Hebei Jing-Jin-Ji Big Data Trading Center	2015	Chengde	Shanxi Data Trading Service Platform	2020	Taiyuan
East-China Jiangsu Big Data Trading Center	2015	Yancheng	Anhui (Huainan) Big Data Exchange Center	2020	Huainan
Wuhan Yangtze River Big Data Exchange Center	2015	Wuhan	The Northern Gulf Big Data Exchange Center	2020	Nanning
Chongqing Big Data Trading Market	2015	Chongqing	Yangtze River Delta Data Factor Circulation Service Platform	2021	Suzhou
Guiyang Big Data Exchange	2015	Guiyan	Hefei Data Factor Circulation Platform	2021	Hefei
Xixian New Area Big Data Exchange	2015	Xi'an	South China International Data Exchange Co., Ltd.	2021	Foshan
Harbin Big Data Exchange Center	2016	Harbin	Hainan Data Product Marketplace	2021	Haikou
Shanghai Data Exchange Center	2016	Shanghai	Deyang Data Exchange Center	2021	Deyang
Qiantang Big Data Exchange Center	2016	Hangzhou	Wuxi Big Data Trading Platform	2022	Wuxi
Guangzhou Data Exchange Platform	2016	Guangzhou	Hunan Big Data Exchange	2022	Changsha
Shenzhen South China Big Data Trading Co., Ltd	2016	Shenzhen	Fujian Big Data Exchange	2022	Fuzhou
Qingdao Big Data Exchange Center	2017	Qingdao	The North data Trading (Service) Center	2023	Tianjin
Weifang Big Data Service Center	2017	Weifang	Northern Jiangsu Big Data Exchange Center	2023	Suqian
Shandong New Kinetic Energy Big Data Trading Center	2017	Jinan	Huaihai Data Exchange Center	2023	Xuzhou
Zhongyuan Big Data Trading Platform	2017	Zhengzhou	Wenzhou Data Exchange Center	2023	Wenzhou
Henan Pingyuan Big Data Trading Center	2017	Xinxiang	Inner Mongolia Big Data Exchange Center	2024	Hohhot

Sources: China Academy of Information and Communications Technology: <Big Data White Paper>; China Academy of Information and Communications Technology: <White Paper on Data Factors (2022)>; publicly available information from provincial and municipal data trading platforms

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On the supply side, data trading platforms provide a diversified array of products and services across multiple domains, including government-open data, enterprise internal data, web-crawled data, and datasets supplied by third parties. They also offer value-added services aligned with market demand. On the demand side, data trading platforms continuously expand into new business fields (Li, 2024), establishing specialized data zones for specific application scenarios and distinctive sectors, thereby effectively unlocking the latent value of data factors. For example, Beijing, Guangdong, Jiangsu, and Zhejiang have advanced the formation of specialized platforms designed to serve as comprehensive hubs for data resuscitation, analysis, trading, circulation, and sharing across finance, industry, healthcare, and other sectors. According to the 2024 China Data Trading Market Research Report, the market size of China's data trading sector reached approximately 1536.9 billion yuan in 2023 (National Engineering Laboratory for Big Data Circulation and Trading Technology, & Shanghai Data Exchange, 2024), indicating that the establishment of data trading platform has significantly stimulated demand for data applications, promoted efficient data circulation, and powerfully unleashed the value of data factors.

Theoretical analysis

Direct impact of the market-oriented allocation of data factors on urban pollution reduction and carbon reduction

Traditional production modes tend to rely on large-scale factor inputs to organize production and expand reproduction, yet they use production factors inefficiently (Li and Zhou, 2021). Under this paradigm, given fixed factor inputs and pollutant emissions, actual output remains low; raising output therefore requires additional inputs, which in turn leads to higher emissions. Reconciling economic growth with environmental protection thus demands the adoption of cleaner production factors or improvements in the efficiency of conventional factors. Compared with traditional inputs, data factors are environmentally friendly because they can be shared instantly, replicated without limit, and yield marginal benefits that far exceed marginal costs (He et al., 2022). In production activities where factor substitutability is relatively high, deploying data factors can raise actual output while reducing pollutant and carbon emissions. Beyond their substitution effect, data factors complement traditional inputs, enhancing factor-use efficiency and resource allocation, thereby transforming energy-intensive, pollution-intensive growth patterns and mitigating local environmental problems. The market-oriented allocation of data factors, first, establishes a data-resource allocation system dominated by market mechanisms that maximizes data value and promotes the integration of data with conventional inputs. Second, it fosters the development of supporting technologies such as big data analytics and cloud computing. Governments can employ these digital tools to monitor pollution and carbon emissions in real time and to compile accurate statistics, reducing information asymmetries in environmental governance and improving efficiency at each stage of pollution reduction and carbon reduction efforts (Wang and Chu, 2023). In addition, the application of digital technologies boosts production and management efficiency, optimizes production processes (Wang et al., 2022), facilitates the combined use of data with labor and capital, and cuts resource waste and emissions in corporate operations. On this basis, the following hypothesis is proposed:

Hypothesis 1: The market-oriented allocation of data factors promotes urban pollution reduction and carbon reduction.

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Market-oriented allocation of data factors, energy-structure optimization, and urban pollution reduction and carbon reduction

The market-oriented development of data factors is usually accompanied by advances in digital technology, and the application of such technology helps popularize new energy sources, increase their share in total consumption, and optimize the energy mix (Wang and Li, 2022). First, the substitution effect generated by data factors reduces the use of highly polluting inputs, thereby promoting cleaner energy consumption (Guo and Wang, 2023). Second, the complementarity between data factors and traditional inputs improves energy efficiency: the energy required per unit of output falls markedly, leading to lower energy use and reduced pollutant and carbon emissions. Moreover, the expansion of big-data analytics and other next-generation information-communication technologies that accompanies the market-oriented allocation of data factors can be applied in energy production and consumption, enabling more accurate supply-and-demand forecasting and further enhancing energy efficiency (Xu et al., 2019). For example, data-dispatch centers in power grids provide real-time monitoring and prediction, increase transmission efficiency, and reduce unnecessary energy use and carbon emissions. The market-oriented allocation of data factors also strengthens firms' capacity to acquire and analyze energy data, giving crucial support to the development of clean energy. Big-data techniques can offer high-precision assessments of the spatial distribution, variability, and annual exploitable volume of renewable resources such as wind and solar power, helping new-energy firms select sites and lay out generating facilities rationally, thus reducing resource waste. This energy-structure effect lowers pollutant and carbon emissions and effectively decouples economic growth from atmospheric emissions.

Hypothesis 2: The market-oriented allocation of data factors promotes urban pollution reduction and carbon reduction by optimizing the regional energy structure.

Market-oriented allocation of data factors, technological innovation, and urban pollution reduction and carbon reduction

The EKC indicates that the technological effect generated by technological change is one of the main channels for improving environmental quality. Yet blocked flows of innovation inputs and low innovation incentives hinder regional technological progress. Because data factors face almost no mobility barriers, combining them with the inputs required for technological innovation helps allocate innovation resources efficiently, raises the enthusiasm of local innovators, and enhances overall innovation capacity. Given this study's focus on urban green development, technological innovation here refers specifically to green technological innovation. First, green innovation depends on the exchange and integration of information across actors and sectors. The market-oriented allocation of data factors improves the information function of data, increases the efficiency of data communication and transfer, strengthens firms' confidence in research and development, and enlarges R&D investment, thereby promoting green innovation (Song et al., 2022). Second, the market-oriented allocation of data factors removes barriers to data acquisition and encourages data circulation and sharing across industries and regions. The technical results derived from data analysis are often reproducible and transferable, generating knowledge spillovers. These spillovers provide firms and research institutions with multi-source heterogeneous data, facilitate cross-domain knowledge integration, and stimulate innovation ideas, which are especially valuable for complex-systems analysis and green technology research and development.

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Finally, green innovation entails long cycles and high risks. By broadening information sources and improving data quality, the market-oriented allocation of data factors enhances managers' ability to identify risks and reduces uncertainty about economic policies and innovation paths, making future policy and technology choices more predictable and increasing firms' risk-bearing capacity (Zheng et al., 2024). In summary, the market-oriented allocation of data factors fosters green technological progress. According to new economic geography, technological innovation and progress raise resource-use efficiency and advance green industrial development (Huang et al., 2018). Technological innovation achieves pollution reduction and carbon reduction through two mechanisms. First, it encourages the adoption of clean energy. The development of photovoltaic, wind, and hydrogen technologies replaces fossil fuels and significantly reduces sulfur-dioxide emissions, while carbon captures and storage directly lower carbon emissions. Second, the application of green technologies in high-efficiency equipment, intelligent control systems, and environmental monitoring and management curtails fossil-fuel consumption, thereby cutting pollutant and carbon emissions. Based on these considerations, this study proposes the following hypothesis.

Hypothesis 3: The market-oriented allocation of data factors promotes urban pollution reduction and carbon reduction by exerting a technological effect.

Market-oriented allocation of data factors, industrial-structure upgrading, and urban pollution reduction and carbon reduction

As a new production factor, data can, first, generate a multiplier effect by integrating deeply with other inputs and driving the efficient consolidation of resources within a city, thereby achieving comprehensive coupling of urban factors. Second, the market-oriented allocation of data factors promotes full data circulation: data-trading institutions pool, combine, and transmit data, dismantling barriers to cross-temporal and cross-organizational flows and fostering equitable regional sharing of resources (Shi et al., 2024). Consequently, this allocation mechanism enables diverse inputs to be combined efficiently, raises factor-allocation efficiency, and helps firms obtain precise information on supply and demand along the entire value chain. Higher efficiency not only improves resource utilization but also forces low-productivity segments to exit the market, directing resources toward innovative, high-end industries and thereby promoting industrial-structure optimization and upgrading (Cao and Yue, 2024). Moreover, the market-oriented allocation of data factors can propel the development of emerging industries such as artificial intelligence, big data, and the Internet of Things, accelerating the shift toward high-technology sectors and further driving structural transformation (Tian and Li, 2022). An optimized industrial structure channels growth into low-carbon, high-value-added, and technology-intensive activities, hastens the reallocation of resources from low-efficiency to high-efficiency sectors, and reduces excessive dependence on environmental resources (Ge, 2022). Specifically, expansion of the tertiary sector and strategic emerging industries lowers the share of highly polluting, energy-intensive sectors in the economy, reducing pollutants and greenhouse-gas emissions at the source. Structural adjustment also motivates firms to adopt eco-friendly production methods, fostering a virtuous cycle between process improvement and environmental quality. On this basis, the study proposes the following hypothesis.

Hypothesis 4: The market-oriented allocation of data factors promotes urban pollution reduction and carbon reduction by driving industrial-structure upgrading.

The logical framework of this study is illustrated in *Figure 1*.

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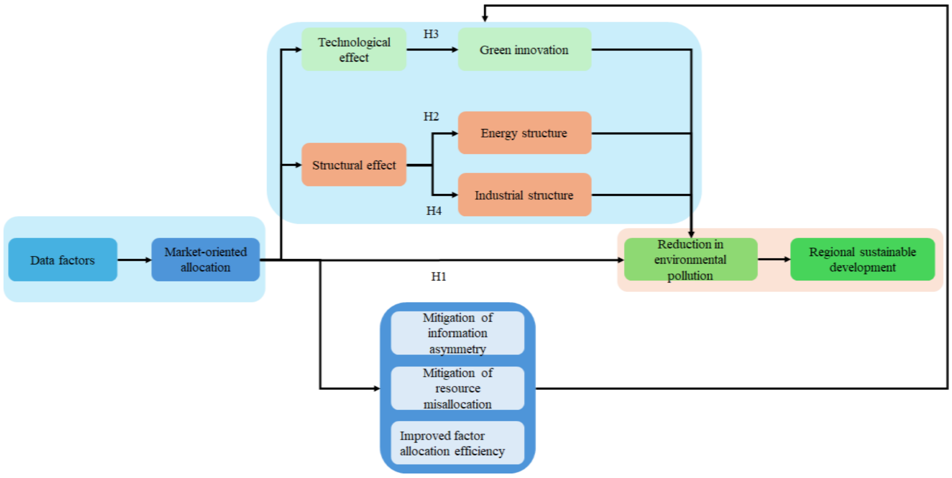

***Figure 1.** Logical framework*

Materials and methods

Methods

To effectively identify the pollution and carbon reduction effects of the market-oriented allocation of data factors, this study treats the establishment of data trading platforms as a quasi-natural experiment that promotes urban emission reduction. Given the phased implementation characteristics of the policy, a multi-period DID approach is employed to evaluate its impact. This method identifies the net effect of data-factor marketization by comparing the changes in the dependent variables between the treatment group and the control group before and after policy implementation. Specifically, cities that established data trading platforms are classified as the treatment group, while cities not affected by the policy are classified as the control group. On this basis, the following econometric model is constructed:

$$Emission_{it} = a + a_1 Datam_{it}(Treat_i \times Post_t) + a_2 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad \text{(Eq.1)}$$

where $Emission_{it}$ denotes either the pollutant emissions or the carbon emissions of city i in year t. $Datam_{it}$ is the core independent variable representing the data trading platform pilot policy. $Treat_i$ is a treatment group dummy variable that takes the value of 1 if city i has established a data trading platform and 0 otherwise. $Post_t$ is a dummy variable indicating the policy implementation period; if a data trading platform is established in year t, $Post_t$ is assigned a value of 1 in that year and thereafter, and 0 otherwise. The interaction term $Datam_{it}$, defined as $Treat_i \times Post_t$, serves as the core variable capturing the net effect of data-factor marketization on urban pollutant emissions and carbon emissions. X_{it} is a vector of control variables that may influence urban pollutant and carbon emissions, with the corresponding coefficient vector a_2. μ_i and δ_t capture city fixed effects and year fixed effects, respectively, and ε_{it} is the random error term.

Materials

Dependent variables

Following the common approach in recent literature, this study uses regional sulfur-dioxide emissions as a proxy for overall pollutant emissions (Li and Zhou, 2021). Sulfur

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dioxide is both a highly representative and a particularly harmful air pollutant, and its data series contain fewer missing observations than those for other pollutants. Industrial sulfur-dioxide emissions are expressed in logarithmic form ($lnSO_2$). Carbon emissions are measured by the natural logarithm of regional carbon-dioxide emissions ($lnCO_2$).

Core independent variable

To capture the exogenous shock associated with government-supported data-trading platforms, a dummy variable, *Datam*, is constructed. For a given city, *Datam* equals 1 in the year that a government-backed data trading platform is established and in every subsequent year; it equals 0 otherwise. During the sample period, thirty-four cities launched government-participation, region-level data-trading platforms. In cities that set up more than one platform, the earliest launch year is used.

Control variables

To control for other regional characteristics affecting pollution and carbon emissions, and drawing on the EKC and related studies, the following variables are included: economic-development scale (*pGDP*), measured by per-capita GDP; industrial scale (*Indcorp*), measured by the number of above-designated-size enterprises; social consumption level (*Consume*), measured by the ratio of total retail sales of consumer goods to GDP; population size (*People*), measured by population per unit of urban land; fiscal expenditure level (*Exp*), measured by the ratio of general public fiscal expenditure to GDP; foreign direct investment intensity (*FDI*), measured by the ratio of actually utilized foreign investment to GDP; human capital (*Educate*), measured by the ratio of undergraduate and junior-college students to total population; and environmental-regulation stringency (*Regulation*), measured by the share of environment-related word frequencies in each city's government work report.

Data sources and variable description

After matching the above variables, prefecture-level city samples from Hong Kong, Macao, Taiwan, and Tibet were excluded due to severe data deficiencies. In addition, samples from Chaohu, Sansha, Haidong, and Danzhou were removed because of administrative boundary adjustments or substantial missing values in key variables. Based on the principles of data availability, consistency, and comparability, a total of 31 city samples were excluded, resulting in a balanced panel dataset of 269 Chinese cities for 2010-2022 is obtained; limited missing observations are filled by interpolation. To eliminate scale differences, the dependent variables and several controls are logarithmically transformed. Detailed definitions and data sources are reported in *Table 2*.

Results

Baseline regression results

Table 3 reports the analysis results concerning the effect of the market-oriented allocation of data factors on urban pollutants and carbon emissions. The estimates in model (1) and model (2) indicate that, irrespective of whether control variables are included, the regression coefficients of the market-oriented allocation of data factors with

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respect to carbon-dioxide emissions are significantly negative, implying an overall negative effect on urban carbon emissions. Similarly, the outcomes in model (5) and model (6) reveal a significant negative impact of the market-oriented allocation of data factors on urban pollutant emissions. According to the coefficients in model (2) and model (6), compared with cities that have not established a data trading platform, those that have done so experience an average reduction of approximately 6.78% in carbon emissions and about 30.98% in sulfur-dioxide emissions. In addition, given that the enabling and integrative effects of data factors on other resources may be subject to temporal lags, the dependent variables carbon emissions and pollutant emissions are further lagged by one and two periods to examine the dynamic impact of the market-oriented allocation of data factors on urban pollutant and carbon emissions; as shown in the results of model (3)-(4) and model (7)-(8) in *Table 3,* as the lag length is extended, the coefficient of the core explanatory variable *Datam* remains significant at the 1% level and tends to increase relative to the static regression results, indicating that data factors can continuously unleash their own efficient and intensive green attributes through factor integration and thereby exert a dynamically strengthening effect on urban pollution reduction and carbon reduction. Based on above analysis, hypothesis 1 is supported.

Table 2. *Variable type, name, symbol, definition, and data source*

Variable type	Variable name	Variable symbol	Variable definition	Data source
Dependent variables	Pollution emission level	*lnSO₂* → $lnSO_2$	Logarithm of industrial sulfur-dioxide emissions in the city	EPS database Statistical yearbooks of each region Statistical bureaus of each city
	Carbon emission level	$lnCO_2$	Logarithm of carbon-dioxide emissions in the city	Crippa et al. (2023)
Core independent variable	Market-oriented allocation of data factors	*Datam*		Big Data White Paper White Paper on Data Factors (2022) Public information released by provincial and municipal data-trading platforms
Control variables	Economic-development scale	*lnpGDP*	Logarithm of per-capita GDP	EPS database China City Statistical Yearbook Statistical yearbooks of each region Statistical bureaus of each city Government work reports of each sample city
	Industrial scale	*lnIndcorp*	Logarithm of the number of above-designated-size enterprises in the city	
	Social consumption level	*Consume*	Ratio of total retail sales of consumer goods to GDP	
	Population scale	*lnPeople*	Logarithm of population per unit of urban land area	
	Fiscal expenditure level	*Exp*	Ratio of general public fiscal expenditure to GDP	
	Foreign direct investment intensity	*FDI*	Ratio of actually utilized foreign direct investment to GDP	
	Human capital	*Educate*	Ratio of undergraduate and junior-college students to total population	
	Environmental-regulation stringency	*lnRegulation*	Logarithm of the ratio of environment-related word frequencies to total word count in each city's government work report	

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Table 3. *Benchmark regression results*

Variables name	$lnCO_2$		$F1.lnCO_2$	$F2.lnCO_2$	$lnSO_2$		$F1.lnSO_2$	$F2.lnSO_2$
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**	**Model (7)**	**Model (8)**
Datam	-0.0693*** (0.0192)	-0.0678*** (0.0178)	-0.0762*** (0.0185)	-0.0855*** (0.0152)	-0.3307*** (0.0586)	-0.3098*** (0.0594)	-0.3356*** (0.0643)	-0.2657*** (0.0663)
lnpGDP		0.0833*** (0.0153)	0.0879*** (0.0167)	0.0800*** (0.0182)		-0.0091 (0.0766)	-0.0200 (0.0798)	-0.0030 (0.0960)
lnIndcorp		0.0490*** (0.0100)	0.0522*** (0.0105)	0.0595*** (0.0107)		0.1127** (0.0551)	0.0897 (0.0557)	0.0892 (0.0625)
Consume		0.1150*** (0.0336)	0.1159*** (0.0387)	0.0981** (0.0426)		0.5975** (0.2380)	0.4861* (0.2642)	0.2305 (0.2686)
lnPeople		0.2151*** (0.0706)	0.2231*** (0.0733)	0.2144*** (0.0740)		0.2209 (0.2736)	0.3089 (0.2697)	0.1718 (0.2965)
Exp		-0.0614 (0.0444)	0.0061 (0.0325)	0.0517 (0.0357)		-0.5413** (0.2583)	-0.3730 (0.2445)	-0.1031 (0.2092)
FDI		-0.3412 (0.2236)	-0.5959** (0.2685)	-0.6281** (0.2938)		-3.3461*** (1.1586)	-3.8070*** (1.1690)	-2.8216** (1.1794)
Educate		0.2277 (0.3038)	0.4817 (0.4116)	0.9226* (0.4817)		0.6228 (1.0922)	1.4124 (1.4199)	3.2015* (1.7555)
lnRegulation		-0.0044* (0.0025)	-0.0047** (0.0024)	-0.0028 (0.0022)		-0.0132 (0.0096)	-0.0102 (0.0103)	-0.0096 (0.0109)
Constant	3.1455*** (0.0018)	2.8717*** (0.2917)	2.8515*** (0.3191)	2.9222*** (0.3366)	9.7055*** (0.0091)	10.4591*** (1.2446)	10.7796*** (1.3074)	10.0156*** (1.4798)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES	YES
Adj-R^2	0.9848	0.9858	0.9867	0.9882	0.8740	0.8753	0.8787	0.8765
N	3497	3497	3228	2959	3497	3497	3228	2959

(1) ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively, with robust standard errors in parentheses. The same as below

Parallel-trend assumption assessment

The multi-period DID model requires that the treatment and control groups satisfy the parallel-trend assumption, that is, pollutant emissions and carbon emissions in pilot and non-pilot cities must follow identical trajectories before the establishment of data trading platform. Following Kong (2022), the event-study approach is employed to test this assumption. *Figures 2a* and *3a* show that, prior to the implementation of the data trading platform policy, there are no significant pre-treatment differences between the treatment and control cities in either carbon-emission levels or pollutant-emission levels, supporting the parallel-trend assumption. After adoption, the coefficients of the data-trading-platform pilot policy are significantly negative at the 10% level and display a dynamically enlarging pattern, indicating a marginally increasing effect of the establishment of data trading platform on urban pollution reduction and carbon reduction.

In addition, when staggered DID models exhibit treatment-effect heterogeneity across groups or over time, traditional two-way fixed-effects DID regressions can yield biased estimates, and negative weights for some units may even reverse the sign of the coefficient, producing results opposite to the true effect. Therefore, this study applies the heterogeneity-robust DID estimators proposed by Sun and Abraham (2021), Gardner (2022), and Freyaldenhoven et al. (2019) to correct potential bias in the conventional staggered DID model. *Figures 2b*, *c, d* and *3b*, *c, d* present the regression results obtained

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with these three heterogeneity-robust estimators; the coefficient of *Datam* turns from positive to negative after policy implementation and the effect strengthens over time. These findings indicate that, after alleviating heterogeneity-related bias, the establishment of data trading platform continues to promote urban pollution reduction and carbon reduction in a stable and robust manner.

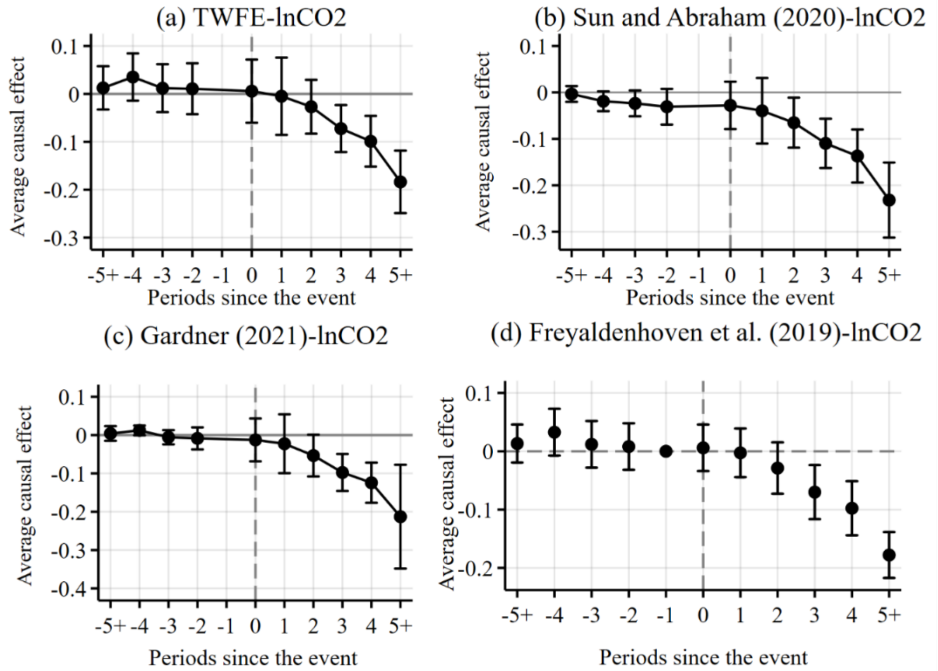

Figure 2. *Parallel trend test (i) All figures report point estimates and 90% confidence intervals. (The same applies to the figures below)*

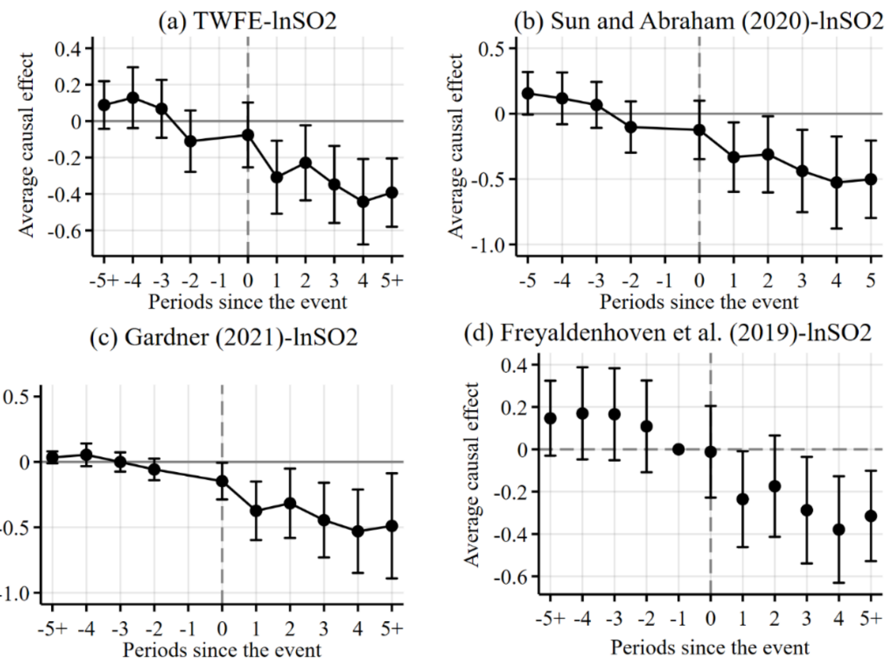

Figure 3. *Parallel trend test (ii)*

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Robustness tests

Placebo test

Although this study has controlled for a wide range of potential variables that may influence urban pollutant emissions within the quasi-natural experimental framework, including economic development level, industrial scale, social consumption level, population size, fiscal expenditure intensity, foreign direct investment intensity, human capital, and environmental regulation intensity, unobserved factors may still exist. For example, economic development is often accompanied by increased energy consumption, which may in turn raise pollution levels; population size is closely associated with energy consumption patterns, transportation demand, and infrastructure construction, all of which can affect carbon and pollutant emissions; government intervention may influence the formulation and enforcement of environmental policies, thereby shaping emission outcomes; and the intensity of environmental regulation reflects a city's commitment to green development and thus also affects environmental performance. Although these considerations have been incorporated into the selection of control variables and other relevant determinants of urban emissions have been included, it remains possible that certain unobserved city-specific characteristics may bias the estimated effects of the innovative city pilot policy, and because treatment timing differs across pilot cities in the multi-period DID framework, it is necessary to generate both a pseudo-treatment-group dummy, $Group^{random}$, and a pseudo-policy-timing dummy, $Post^{random}$, by randomly assigning a policy year to each observation. Following Bai et al. (2022), Stata is used to construct 500 random shocks of a pseudo-pilot policy for all sample cities; each iteration selects the same number of treated cities, and the policy timing is randomly drawn, yielding 500 pseudo variables, $Datam^{random}$ ($Group^{random} \times Post^{random}$). The kernel density of the 500 β^{random} estimates and their p-value distribution are displayed in *Figure 4a, b*. The β^{random} coefficients generated during the randomization are clustered around zero, and most p-values exceed 0.05, whereas the actual policy coefficients are -0.0678 and -0.3098, markedly different from the placebo results. This indicates that the quantitative findings are not driven by this potential factor and are therefore robust.

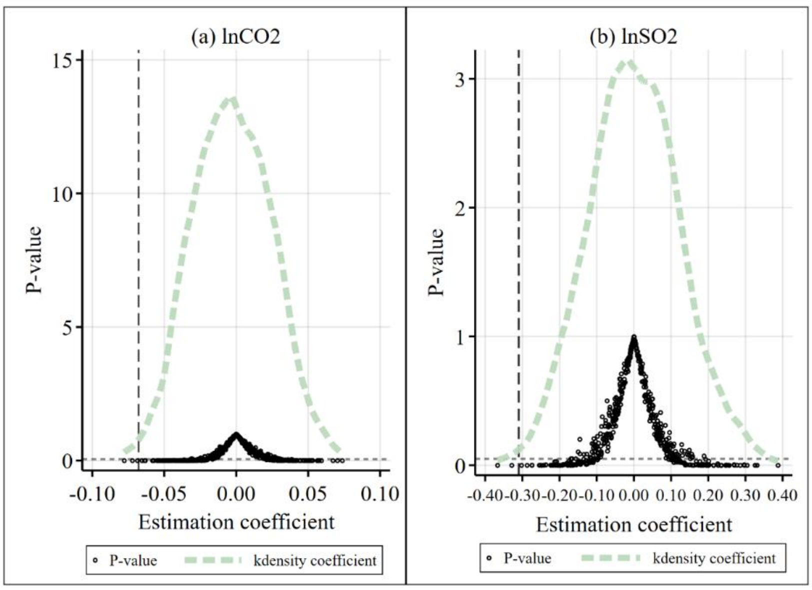

Figure 4. *Placebo test*

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Endogeneity

(1) PSM-DID. Considering that cities selected to establish data trading platforms may already possess a stronger digital economy base, selection bias could influence the estimation results. Therefore, a PSM-DID approach is adopted to alleviate potential sample-selection bias. Specifically, a logit or probit model is employed to estimate the probability that each sample city enters the treatment group, namely the propensity score. Based on these estimated scores, control group cities with similar characteristics are matched to the treatment group, ensuring that the two groups exhibit comparable distributions across covariates. This procedure mitigates selection bias and alleviates systematic differences in observable characteristics between the treatment and control groups. After matching, the DID model specified in *Equation 1* is re-estimated to obtain the policy treatment effect. Specifically, in order to enhance the robustness of the PSM-DID estimation, this study using 1:4 nearest-neighbor matching, radius matching, and kernel matching, each treated city is paired with suitable control cities; the covariates for matching are economic development scale, industrial scale, social consumption level, population size, fiscal expenditure level, foreign direct investment intensity, human capital, and environmental regulation stringency. Balance tests are performed on the selected covariates to confirm their appropriateness (for brevity, only the balance test for 1:4 nearest-neighbor matching is reported; the others are available on request). The results, as shown in *Table 4,* indicate that the propensity-score-matching process effectively mitigates self-selection bias, and subsequent regressions based on the matched sample are justified. The corresponding regression outcomes appear in *Table 5,* models (1)-(6); the coefficient on *Datam* remains significantly negative, confirming the robustness of the core conclusion that the market-oriented allocation of data factors exerts a new-quality-productivity effect, promotes urban pollution reduction and carbon reduction, and advances the green transformation of the economy and society.

Table 4. *Balance test*

Variables name		**Mean**		**Bias**	**Reduct bias**	**t**	**t-test (p > t)**
		Treated	**Control**				
lnpGDP	Unmatched	11.243	10.689	103.0	97.8	19.32	0.000
	Matched	11.243	11.255	-2.2		-0.36	0.717
lnIndcorp	Unmatched	1.200	0.706	61.9	80.1	12.29	0.000
	Matched	1.200	1.298	-12.3		-1.64	0.102
Consume	Unmatched	0.412	0.380	32.8	87.8	6.04	0.000
	Matched	0.412	0.408	4.0		0.61	0.545
lnPeople	Unmatched	-2.751	-3.391	88.0	97.5	15.98	0.000
	Matched	-2.751	-2.767	2.2		0.39	0.698
Exp	Unmatched	0.240	0.267	-34.0	82.1	-5.91	0.000
	Matched	0.240	0.245	-6.1		-1.02	0.309
FDI	Unmatched	0.021	0.013	52.8	70.7	10.57	0.000
	Matched	0.021	0.023	-15.5		-2.12	0.034
Educate	Unmatched	0.051	0.016	116.5	98.2	28.31	0.000
	Matched	0.051	0.052	-2.1		-0.24	0.809
lnRegulation	Unmatched	-5.156	-5.006	-18.8	85.6	-3.02	0.003
	Matched	-5.156	-5.134	-2.7		-0.64	0.525

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Table 5. *PSM-DID and 2SLS estimation results*

Variables name	Nearest neighbor matching (1:4)		Radius matching		Kernel matching		First-stage	Second-stage	Second-stage
	lnCO₂	***lnSO₂***	***lnCO₂***	***lnSO₂***	***lnCO₂***	***lnSO₂***	***Datam***	***lnCO₂***	***lnSO₂***
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**	**Model (7)**	**Model (8)**	**Model (9)**
Datam	-0.0389** (0.0191)	-0.1829*** (0.0653)	-0.0638*** (0.0180)	-0.3141*** (0.0587)	-0.0624*** (0.0162)	-0.3099*** (0.0517)	0.0267*** (0.0052)		
IV_Access								-0.2304** (0.1148)	-1.5157* (0.8036)
Constant	2.8672*** (0.3310)	10.3316*** (1.6209)	2.8812*** (0.2912)	10.8305*** (1.2478)	2.7801*** (0.2602)	8.7243*** (1.1194)	2.5803*** (0.4097)		
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Underidentification test							25.244***		
Weak identification test							29.153(16.38)		
Adj-R^2	0.9810	0.9020	0.9852	0.8848	0.9848	0.8859	0.4514	0.6072	0.1943
N	1231	1231	3345	3345	3331	3331	3450	3450	3450

(1) The value in parentheses for the F-statistic indicates the critical value for the 10% bias threshold in weak instrument tests

(2) Instrumental-variable regression. Because potential endogeneity may exist between the market-oriented allocation of data factors and urban pollutant and carbon emissions, an instrumental-variable approach is further employed. Following Huang et al. (2019), the number of fixed telephones per one hundred people in each city in 1984 serves as an appropriate instrument. The data are obtained from the <*China City Statistical Yearbook*> and the statistical bulletins released by the respective sample cities. On one hand, the establishment of data trading platforms depends on a city's level of informatization, and cities with historically higher telephone penetration possessed advantages in information-infrastructure construction, making them more suitable sites for such platforms; on the other hand, historical telephone penetration is unlikely to directly affect current pollutant and carbon emissions, satisfying the exogeneity requirement. To construct a panel instrument, the sample cities' internet-broadband penetration rates are introduced as a time-varying factor, and the interaction of each city's 1984 telephone penetration with its contemporaneous broadband penetration, plus one, is logged to create *IV_Access*. Two-stage least squares estimation is then performed. *Table 5,* models (7)-(9), reports the results, which show that the establishment of data trading platforms remains significantly negatively associated with pollutant and carbon emissions; the Kleibergen–Paap rk Wald F-statistics reject the null hypothesis of weak instruments, further validating the baseline findings.

Excluding the influence of other policies

According to Li and Zhou (2021), Li and Wen (2025), and Jiang and Deng (2025), the Broadband China pilot policy, the low-carbon city pilot policy, and the new-energy demonstration city construction policy exert synergistic suppressive effects on urban pollutant and carbon emissions. Therefore, to remove the possible impact of these

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policies, the "Broadband-China" pilot policy (*Broadband*), the low-carbon city pilot policy (*LC*), and the new-energy demonstration city construction policy (*NEDC*) are incorporated into the baseline model, and the regression results are reported in *Table 6*. The findings show that, after controlling these three concurrent policy shocks, the estimated coefficient of the core independent variable remains significantly negative, once again confirming the robustness of the baseline conclusion that the market-oriented allocation of data factors significantly reduces regional pollutant and carbon emission levels.

Table 6. *Robustness test of excluding policy interference in the same period*

Variables name	$lnCO_2$	$lnSO_2$	$lnCO_2$	$lnSO_2$	$lnCO_2$	$lnSO_2$	$lnCO_2$	$lnSO_2$
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**	**Model (7)**	**Model (8)**
Datam	-0.0652***	-0.2982***	-0.0683***	-0.3192***	-0.0661***	-0.2974***	-0.0644***	-0.2963***
	(0.0176)	(0.0585)	(0.0178)	(0.0597)	(0.0179)	(0.0590)	(0.0177)	(0.0586)
Broadband	-0.0242***	-0.1101***					-0.0241***	-0.1126***
	(0.0066)	(0.0349)					(0.0065)	(0.0347)
LC			-0.0115	-0.2024***			-0.0132	-0.2114***
			(0.0137)	(0.0520)			(0.0136)	(0.0516)
NEDC					-0.0118	-0.0869**	-0.0099	-0.0803*
					(0.0088)	(0.0436)	(0.0088)	(0.0437)
Constant	2.9613***	10.8672***	2.8667***	10.3708***	2.8781***	10.5063***	2.9605***	10.8282***
	(0.2919)	(1.2638)	(0.2905)	(1.2426)	(0.2913)	(1.2461)	(0.2904)	(1.2627)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES	YES
$Adj\text{-}R^2$	0.9858	0.8756	0.9858	0.8759	0.9858	0.8754	0.9858	0.8764
N	3497	3497	3497	3497	3497	3497	3497	3497

Additional robustness tests

(1) Excluding the pandemic period and removing provincial-capital cities. The COVID-19 shock may have introduced volatility into regional carbon and pollutant emissions from 2020 onward. The sample period is therefore restricted to 2010-2019. In addition, because municipalities directly under the central government and provincial-capital cities have higher administrative status, these cities are excluded to alleviate possible endogeneity; only ordinary prefecture-level cities are retained. As reported in *Table 7,* models (1) and (2), the market-oriented allocation of data factors continues to produce a significant pollution-reduction and carbon-reduction effect after controlling other factors and external events.

(2) Replacing the dependent variables. To address the potential limitation of using absolute pollutant and carbon emissions in *Equation 1*, the study first replaces the dependent variable in *Equation 1* with carbon emission intensity (*lnCO2_int*) and sulfur dioxide emission intensity (*lnSO2_int*) for re-estimation. *Table 7,* models (3) and (4), shows that the market-oriented allocation of data factors effectively lowers both carbon-emission intensity and pollutant-emission intensity. These findings indicate that the policy helps cities meet total-emission targets and intensity-control targets, providing new momentum for fulfilling dual-control requirements.

Furthermore, urban pollution levels are alternatively measured using PM2.5 data released by the National Tibetan Plateau Data Center of China, as well as industrial smoke

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and dust emissions and industrial wastewater discharge data from the <*China City Statistical Yearbook*>. All variables are logarithmically transformed and substituted into *Equation 1* as the dependent variables for re-estimation. As reported in *Table 7,* models (5) through (7), the coefficient of *Datam* remains significantly negative at least at the 5% level, further confirming that the market-oriented allocation of data factors exerts a significant pollution-reduction effect on cities.

(3) Adding fixed effects and accounting for city-time-varying factors. Because historical, cultural, geographic, and resource endowments differ widely across cities and may change over time, a city-specific time trend is added to *Equation 1*. To further eliminate the influence of provincial policy environments and locational characteristics, city and year fixed effects as well as province-by-year interaction fixed effects are included. *Table 7,* models (8) and (9), reports that, under these stronger controls, the market-oriented allocation of data factors still exerts a significant suppressive effect on urban pollutants and carbon emissions, confirming the robustness of the results.

Table 7. *Robustness test of changing sample structure*

Variables name	***lnCO_2***	***lnSO_2***	***lnCO_2_int***	***lnSO_2_int***	***lnPM2.5***	***lnSmoke***	***lnWater***	***lnCO_2***	***lnSO_2***
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**	**Model (7)**	**Model (8)**	**Model (9)**
Datam	-0.0247*	-0.2091*	-0.1532***	-0.3952***	-0.0300**	-0.1743**	-0.2818***	-0.0209***	-0.1489**
	(0.0143)	(0.1232)	(0.0200)	(0.0610)	(0.0136)	(0.0711)	(0.1038)	(0.0072)	(0.0671)
Constant	2.3403***	9.2504***	-9.6517***	-2.0643	3.0626***	15.0699***	10.2998***	1.6966***	7.2453***
	(0.2192)	(1.5100)	(0.5576)	(1.3332)	(0.2584)	(1.5636)	(1.0631)	(0.1697)	(1.4357)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Prov×Year FE	NO	NO	NO	NO	NO	NO	NO	YES	YES
City×Time Trend	NO	NO	NO	NO	NO	NO	NO	YES	YES
Adj-R^2	0.9932	0.8577	0.9579	0.9039	0.9210	0.8001	0.8627	0.9962	0.8934
N	2390	2390	3497	3497	3497	3497	3497	3401	3401

Heterogeneity analysis

(1) Data-processing efficiency. Because data factors are virtual, their use cannot mirror that of traditional resources such as capital, labor or land; instead, a certain level of digital-infrastructure support is required. A region's capability to process and apply data therefore largely determines whether the green-empowering effect of data factors can be realized. Where abundant data resources exist but appropriate processing and analytical channels are absent, the positive externalities of data factors cannot be fully unlocked. By contrast, big-data technology can mine the myriad associations embedded in data factors and release their value. Therefore, in accordance with the <*Action Outline for Promoting the Development of Big Data*> and the list of the second batch of National Big Data Comprehensive Pilot Zones jointly announced by the National Development and Reform Commission, the Ministry of Industry and Information Technology, and the Cyberspace Administration of China, including Guizhou, Beijing, Tianjin, Hebei, Inner Mongolia, Liaoning, Henan, Shanghai, Chongqing, and Guangdong, cities located within these designated regions are classified as high data-processing efficiency samples, while the remaining cities are categorized as low data-processing efficiency samples, in order to explore the heterogeneous effects of regional data-processing capacity on the relationship

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between the market-oriented allocation of data factors and pollutant and carbon emissions. *Table 8,* models (1) and (2) and models (7) and (8), show that regions with high data-processing efficiency derive a significant pollution-reduction and carbon-reduction effect from the market-oriented allocation of data factors. This finding indicates that building data centers and expanding computing power are fundamental preconditions for exerting the positive externalities of the market-oriented allocation of data factors. Conversely, a lack of analytical capability heightens the dissipation of data resources, preventing cities from using the empowering, superimposing and multiplier effects of data factors to optimize resource-allocation efficiency and achieve pollution reduction and carbon reduction.

(2) Digital-talent agglomeration. The establishment of data trading platform depends on the widespread involvement of compound talents skilled in data analysis, data management and data operations; hence differences in urban stocks of digital human resources influence the pollution-reduction and carbon-reduction role of the market-oriented allocation of data factors. On this basis, this study measures the level of digital talent by calculating the proportion of employees in the information transmission, software, and information technology services sector relative to the total number of employees in each sample city each year. The median value of this indicator across sample cities is then computed, and cities with values above the median are classified as high digital-talent agglomeration cities, while those below the median are classified as low digital-talent agglomeration cities. This classification is used to examine the heterogeneous effects of the market-oriented allocation of data factors under different levels of digital-talent endowment. *Table 8,* models (3) and (4) and models (9) and (10), report that the establishment of data trading platform markedly lowers pollutant and carbon emissions in high-talent cities. This suggests that nurturing and attracting people proficient in digital skills and actively engaged in digital applications can narrow a city's internal digital-application gap, facilitate the sharing and circulation of high-quality data factors, enhance the multiplier effect of data factors, raise resource-allocation efficiency and strengthen the pollution-reduction and carbon-reduction effect of the market-oriented allocation of data factors.

(3) Digital-technology level. The valorization of data factors relies on regional digital-technology capacity. Big data, artificial intelligence and cloud computing are key vehicles for precise analysis, efficient processing and rapid circulation of data factors. Higher digital-technology levels and stronger innovation capacities foster data openness and sharing, standardize data quality and optimize data-use efficiency, thereby enhancing the green-empowering role of the market-oriented allocation of data factors. In this regard, based on the *<Patent Classification System for Key Digital Technologies (2023)>* issued by the China National Intellectual Property Administration and the corresponding IPC reference table, this study identifies and aggregates the number of invention patent applications in each prefecture-level city that are related to digital technologies such as the internet, big data analytics, cloud computing, artificial intelligence, blockchain, and the Internet of Things. This indicator directly reflects differences in regional digital technology development levels. According to the median number of digital-technology-related patent applications among sample cities, the sample is divided into two groups: a high-level group and a low-level group. *Table 8,* models (5) and (6) and models (11) and (12), show that the establishment of data trading platform produces a more pronounced pollution-reduction and carbon-reduction effect in regions with higher digital-technology levels. This result indicates that advances in digital technology are essential for data-factor trading and circulation, help dismantle integration barriers between data factors

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and traditional production factors, accentuate the superimposing and multiplier effects of data factors and further reduce pollutant and carbon emissions.

Table 8. *Heterogeneity analysis results*

Variables name	$lnCO_2$					
	Data-processing efficiency		**Digital-talent agglomeration**		**Digital-technology level**	
	High	**Low**	**High**	**Low**	**High**	**Low**
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**
Datam	-0.1369*** (0.0206)	-0.0315 (0.0219)	-0.0644*** (0.0146)	-0.0021 (0.0409)	-0.0813*** (0.0250)	-0.0398 (0.0379)
Constant	2.5342*** (0.2590)	4.5788*** (0.4328)	3.5060*** (0.2868)	3.5974*** (0.4348)	3.8744*** (0.3540)	0.6839 (0.8798)
Control variables	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Permutation test	0.105**		0.062*		0.042*	
Adj-R^2	0.9906	0.9845	0.9917	0.9871	0.9758	0.9703
N	910	2587	1339	2158	1742	1755
Variables name	$lnSO_2$					
	Data-processing efficiency		**Digital-talent agglomeration**		**Digital-technology level**	
	High	**Low**	**High**	**High**	**Low**	**High**
	Model (7)	**Model (8)**	**Model (9)**	**Model (10)**	**Model (11)**	**Model (12)**
Datam	-0.2394** (0.1050)	-0.0913 (0.1612)	-0.4664*** (0.1517)	-0.0233 (0.1767)	-0.2927*** (0.0616)	-0.0247 (0.2628)
Constant	14.5270*** (1.9420)	20.7436*** (2.6778)	9.9938*** (2.5598)	19.7544*** (3.5476)	8.4534*** (1.4443)	18.0499*** (2.5114)
Control variables	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Permutation test	0.148**		0.443**		0.268**	
Adj-R^2	0.8976	0.5867	0.6083	0.7090	0.8935	0.8597
N	910	2587	1339	2158	1742	1755

Mechanism analysis

Based on the foregoing theoretical analysis and considering that the market-oriented allocation of data factors may lower urban pollutant emissions and carbon emissions through the energy-structure optimization effect, the technological innovation effect, and the industrial-structure upgrading effect, this paper, following the method of Jiang (2022), constructs the following mechanism verification equations to examine the energy structure optimization effect, the technological innovation effect, and the industrial structure upgrading effect of the market-oriented allocation of data factors; in the

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equations, M_{it} denotes the mediating variable, β, β_1, and β_2 are parameters to be estimated. Among them, β_1 is the key coefficient in the mechanism analysis, as it reflects the effect of the market-oriented allocation of data factors on the mediating variable. If $\beta_1 > 0$, it indicates that the market-oriented allocation of data factors promotes urban pollution and carbon reduction through a positive effect on the mediating variable. If $\beta_1 < 0$, it suggests that the market-oriented allocation of data factors facilitates urban pollution and carbon reduction through a negative effect on the mediating variable, and the other variables are defined as in *Equation 1*.

$$M_{it} = \beta + \beta_1 Datam_{it} + \beta_2 X_{it} + \mu_i + m_t + \varepsilon_{it} \quad \text{(Eq.2)}$$

(1) Energy structure optimization effect. Following Kou and Xu (2025), the present study measures the energy structure optimization effect of the market-oriented allocation of data factors with two indicators: city-level energy consumption per unit of GDP (*Energy_ef*) and per-capita regional energy consumption (*Energy_avg*). As shown in *Table 9,* models (1) and (2), a higher degree of market-oriented allocation of data factors is associated with significant declines in both energy intensity and energy use, indicating a marked improvement in energy-use efficiency. In other words, data marketization accelerates informatization and intelligent applications in energy management, precisely identifies and optimizes energy-loss links in production and use, and guides the energy consumption structure toward greater efficiency and conservation, effectively curbing fossil fuel use and achieving energy-saving and emission-reduction synergies. Hypothesis 2 is therefore supported.

(2) Technological innovation effect. The theoretical analysis indicates that the market-oriented allocation of data factors drives pollution reduction and carbon reduction by promoting green technological innovation. Green patents involve inventions related to environmental protection, energy conservation, and resource recycling, and thus proxy green-technology innovation. Using the approach of Li (2020), the international patent-classification green list defines green patents. The number of green invention patent applications (*Gpatqual*) and the number of green utility model patent applications (*Gpatqty*) represent the "quality" and "quantity" of green innovation, respectively, allowing an integrated examination of how the market-oriented allocation of data factors influences both aspects. *Table 9,* models (3) and (4), shows that the coefficients on the market-oriented allocation of data factors are positive and significant at the 5% level or better, meaning that a higher degree of marketization raises a city's green innovation capacity and significantly promotes both the quantity and quality of green technological innovation. Specifically, green invention patents reflect high value, highly novel technical achievements; data marketization fosters the application of big-data analytics and artificial intelligence in the environmental field, strengthening firms' R&D capacity and innovation incentives and thereby advancing high-quality green technologies. Green utility model patents relate mainly to improvements and optimizations at the application level; their shorter development cycles and lower costs allow rapid iterations in energy saving, emission reduction, and efficient resource use. Overall, the market-oriented allocation of data factors encourages firms to improve processes quickly and generate practical green technologies. Green technologies, through efficient gas treatment, wastewater purification, and solid-waste reutilization, reduce harmful emissions, while carbon capture, storage, and utilization directly lower greenhouse-gas intensity, helping cities meet pollution-reduction and carbon-reduction targets. Hypothesis 3 is thus confirmed.

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(3) Industrial structure upgrading effect. According to Yuan and Zhu (2018), industrial structure upgrading is gauged from the perspectives of industrial-structure sophistication and industrial structure rationalization, using the following model to quantify both dimensions. In the model, $Upgrade_{it}$ denotes industrial-structure sophistication, $Theil_{it}$ denotes industrial-structure rationalization, q_{ijt} is the share of the value added of sector j (j = 1,2,3) in city i in year t relative to GDP, and l_{ijt} is the share of employment in sector j in city i in year t relative to total employment, reflecting the sector's labor-market share. *Table 9,* models (5) and (6), present the structural-effect tests. The coefficient on the core independent variable *Datam* is significantly positive, indicating that greater marketization of data factors helps heighten and rationalize industrial structure, pushing urban industries toward higher-value-added segments. The market-oriented allocation of data factors promotes information flow, data sharing, and cross-industry knowledge fusion, thereby fostering high-tech industries and modern services, accelerating the expansion of the tertiary sector and the rise of technology-intensive activities, and optimizing labor-market structure and resource distribution across industries. It effectively steers overall economic structure toward low-carbon, environmentally friendly directions, reducing pollutant and carbon emissions through a pronounced industrial-structure upgrading effect. Hypothesis 4 is therefore supported.

Table 9. *Impact mechanism test*

Variables name	Energy structure optimization effect		Technological innovation effect		Industrial structure upgrading effect	
	Energy_ef	***Energy_avg***	***Gpatqty***	***Gpatqual***	***Upgrade***	***Theil***
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**
Datam	-0.2004***	-0.1535***	0.0078***	0.0047**	0.0083**	0.1456*
	(0.0242)	(0.0244)	(0.0020)	(0.0020)	(0.0036)	(0.0826)
Constant	-2.0987***	-2.8434***	0.1314***	0.1775***	0.4414***	-2.7753**
	(0.5589)	(0.5746)	(0.0406)	(0.0609)	(0.0452)	(1.4138)
Control variables	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
$Adj\text{-}R^2$	0.8618	0.9245	0.3057	0.3981	0.8878	0.8336
N	3497	3497	3497	3497	3497	3497

Extension analysis

Regional welfare effects

"Pollution reduction and carbon reduction" is an important link in the green transformation of the economy and society and a procedural embodiment of green development. However, green development must ultimately achieve a synergy between pollutant abatement and economic growth, not merely a reduction in harmful gas emissions. As a new production factor, data factors possess verified positive environmental externalities, and their empowerment of traditional production factors can also stimulate sustained regional economic growth (Zhao, 2025). Whether data factors, while suppressing regional pollutants and carbon emissions, can further promote coordination between environmental protection and economic growth requires

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investigation. Green total factor productivity denotes the win-win outcome of economic development and ecological protection that is achieved through technological progress, managerial optimization, and institutional innovation under resource and environmental constraints. Following Sun and Yang (2020), this paper calculates regional green total factor productivity (*GTFP*) and replaces the dependent variable in *Equation 1* with *GTFP* to examine the economic consequences of the market-oriented allocation of data factors. *Table 10,* models (1) and (2), shows that the market-oriented allocation of data factors overcomes the drawback of traditional environmental-regulation policies, which tend to sacrifice economic growth temporarily while promoting environmental protection. Enabled by the market-oriented allocation of data factors, cities can reduce undesirable outputs such as pollutant emissions, guide economic and social development toward environmental friendliness, significantly increase desirable outputs, and drive high-quality regional economic growth, thereby advancing the economy and society toward genuine green and sustainable development.

Table 10. *Further discussion*

Variables name	*GTFP*		Capital factor distortion	Labor factor distortion	Market distortion	Resource misallocation
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Datam	0.1289***	0.1158***	-0.2257**	-0.1308**	-0.1517***	-0.0500***
	(0.0135)	(0.0131)	(0.0894)	(0.0519)	(0.0538)	(0.0159)
Constant	0.3412***	0.4936**	1.4608	-3.9065***	-0.8965	0.8654***
	(0.0014)	(0.2211)	(1.0529)	(0.9894)	(0.8061)	(0.2675)
Control Variables	NO	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Adj-R^2	0.6668	0.6754	0.5659	0.7646	0.5041	0.5737
N	3458	3458	3203	3203	3203	3203

Resource-allocation optimization effect

Problems such as information asymmetry led to factor distortions and resource misallocation, wasting and over-consuming resources so that they cannot be used to their fullest, which further harms the environment. The market-oriented allocation of data factors promotes efficient data circulation, breaks informational cocoons and industry information barriers, and facilitates the agglomeration of high-value factors; while sharply easing information asymmetry, it also improves the matching efficiency between factor suppliers and demanders, empowers traditional factors through the free flow of data, raises the efficiency of market resource allocation, and reduces resource misallocation, ultimately forming a virtuous cycle of "free flow of data factors → urban pollution reduction and carbon reduction → lower factor distortions and resource losses → further urban pollution reduction and carbon reduction." Accordingly, drawing on the calculation methods of Chen and Hu (2011) and Yu and Shen (2024), this paper measures capital-factor distortion, labor factor distortion, market distortion, and the resource-misallocation index for the sample cities to gauge optimization of urban resource allocation; except for the resource-misallocation index, the logarithms of these measures replace the dependent variable in *Equation 1* to test whether the market-oriented allocation of data factors, while driving regional pollution reduction and carbon

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reduction, can also optimize resource allocation and reduce resource distortions. As shown in *Table 10,* models (3)-(6), an improved market-oriented data-factor mechanism strengthens factor mobility, ensures that economic agents obtain accurate market information, enhances decision accuracy, significantly reduces distortions in capital, labor, and other production factors, and mitigates resource misallocation. Moreover, by regulating data trading and clarifying property rights, data-factor marketization creates a transparent and fair market environment for enterprises and reinforces the market's primary role in resource allocation, enabling resources to be better deployed through competition and thereby improving allocation efficiency. Ultimately, it further cuts regional resource losses and supports urban reductions of pollutants and carbon emissions.

Discussion

Existing studies on the green effects of the market-oriented allocation of data factors have primarily focused on energy efficiency, such as Yang (2025). In contrast, this study finds that the market-oriented allocation of data factors significantly reduces urban pollutant emissions and carbon emissions, with a dynamically increasing governance effect over time. The underlying mechanism operates through multiple channels. First, the establishment of data trading platforms and the advancement of market-oriented data allocation reduce transaction costs associated with cross-entity and cross-regional data flows, thereby improving the efficiency of information identification, monitoring feedback, and resource matching. This enables governments, firms, and market actors to more promptly identify high energy-consuming and high-emission segments, providing more precise decision support for pollution control and carbon mitigation. In this sense, data factors are not merely informational resources but are transformed into foundational inputs for green development. Second, the three transmission mechanisms identified in this study, namely energy structure optimization, technological innovation, and industrial structure upgrading, demonstrate that the impact of market-oriented data allocation extends beyond monitoring and governance to deeply empower urban green transformation. At the energy level, enhanced data circulation strengthens monitoring, analysis, and scheduling capabilities in energy use, thereby improving energy efficiency. At the innovation level, data sharing and integration enhance knowledge spillovers, technological diffusion, and biased technological progress, as suggested by Liao and Ru (2024), facilitating a shift in green innovation from quantitative expansion to qualitative improvement and reinforcing the endogenous technological drivers of pollution and carbon reduction. At the industrial level, as a highly mobile and permeable production factor, data accelerates the digital transformation of traditional industries and the agglomeration of high value-added sectors, as shown by Zhan et al. (2025), promoting a more advanced and coordinated industrial structure. Overall, this study not only confirms the pollution and carbon reduction effects of market-oriented data allocation but also reveals a multi-level transmission logic characterized by resource optimization, technologically biased progress, and structural upgrading, thereby enriching the literature on the digital economy, urban sustainability, and factor market reform.

Furthermore, the heterogeneity and extended analyses deepen the interpretation of the baseline results. On the one hand, data factors do not automatically translate into environmental performance. Their multiplier effect on environmental governance depends on whether local regions possess the capacity to transform data resources into

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governance capability, innovation capability, and development capability. In other words, the environmental dividends of market-oriented data allocation can only be realized when combined with robust digital infrastructure, abundant digital human capital, and strong digital technology application capacity. On the other hand, the impact of market-oriented data allocation is not confined to the environmental domain but extends to improvements in resource allocation efficiency and high-quality development. This indicates that data factor market reform embodies dual value in pollution and carbon reduction as well as quality and efficiency enhancement. It reduces undesirable outputs while increasing desirable outputs, demonstrating the compatibility between green transformation and economic growth. These findings provide direct policy implications for local governments seeking to advance data trading platforms, refine data property rights and circulation rules, strengthen digital talent cultivation, and empower green urban development through digital technologies.

Nevertheless, this study has certain limitations. It examines the green development effects of market-oriented data allocation at the city level, while the long-term performance consequences of data trading platform construction require validation with longer time-series data. In addition, due to data availability constraints, this study does not explore how the integration of new production factors into firm-level production functions influences micro-level behavioral choices. Future research will address these limitations by incorporating longer-term data and conducting micro-level analyses to further investigate the mechanisms and consequences of data factor market reform.

Conclusions

Conclusions

In recent years, the large-scale construction and high-quality, healthy development of data-trading venues have opened cross-temporal and cross-spatial channels for the circulation of data factors. Driven by market-oriented allocation instruments, the multiplier effect of data factors has been fully unleashed, laying the foundation and creating the possibility for urban energy conservation and emissions reduction in the course of green transformation. Using the establishment of data trading platform as a quasi-natural experiment and panel data for 269 Chinese cities from 2010 to 2022, this paper builds a multi-period difference-in-differences model to examine in depth the influence and internal mechanisms of the market-oriented allocation of data factors on urban pollutant and carbon emissions. The main conclusions are as follows. First, the market-oriented allocation of data factors significantly suppresses urban pollutants and carbon emissions, and this suppressive effect increases dynamically over time; a series of robustness tests confirm this finding. Second, mechanism analysis shows that the market-oriented allocation of data factors produces an energy-structure optimization effect, markedly improving urban energy-use efficiency and reducing total energy consumption; a technological-innovation effect, strengthening urban green-technology innovation capacity and promoting both the quantity and the quality of green innovation; and an industrial-structure upgrading effect, guiding urban industries toward greater sophistication and rationalization, ultimately cutting pollutant and carbon emissions and realizing green economic and social transformation. Third, the pollution-reduction and carbon-reduction effect of the market-oriented allocation of data factors is more pronounced in regions with high data-processing efficiency, strong digital-talent agglomeration, and advanced digital-technology levels. Finally, further analysis reveals

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that, under the market-oriented allocation, the circulation of data factors can enhance the overall level of green economic development in cities, increasing desirable outputs while reducing undesirable outputs such as pollutants and carbon dioxide. It can also effectively lessen distortions in local production factors such as capital and labor, mitigate resource misallocation, and strengthen the market's primary role in resource allocation, thereby providing an inexhaustible driving force for high-quality regional economic and social development.

Policy recommendations

Based on the above conclusions, the following policy insights are offered. First, government should accelerate the construction of an institutional foundation for the market-oriented allocation of data factors by improving key mechanisms such as data-property-rights protection, data pricing, and transaction supervision, thereby ensuring the lawful circulation and rational use of data in the market. Cross-industry and cross-regional exchange and flow of data resources should be encouraged to help enterprises obtain high-quality data on environmental protection and production optimization, improving the scientific rigor and precision of environmental decisions. At the same time, high-emission enterprises should be required to connect to data platforms so that environmental data are uploaded in real time and monitored dynamically, providing governments with timely information for emissions supervision and carbon-market regulation. Second, data resources should be embedded in the green-technology-innovation system to assist cities in achieving breakthroughs in pollution-reduction and carbon-reduction targets. Third, the market-oriented allocation of data factors should be used to coordinate industrial-structure upgrading and energy-use optimization. On the industrial side, fiscal incentives can support enterprises in adopting digital production systems and intelligent supply-chain management tools, eliminating backward capacity that is highly polluting and inefficient in data use and guiding industries toward high-technology, high-value-added fields. On the energy side, governments should vigorously promote data-based energy management systems, such as industrial energy efficiency management platforms and urban energy consumption visualization systems, to raise energy-use efficiency and achieve fine-grained energy allocation and optimized management, thereby enhancing overall pollution-reduction and carbon-reduction performance.

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REFERENCES

[1] Bai, J., Zhang, Y., Bian, Y. (2022): Does innovation-driven policy enhance urban entrepreneurial activity? Empirical evidence from the national innovative city pilot. – China Industrial Economics 6: 61-78.
[2] Cao, Z., Yue, Z. (2024): The impact of digital-and-real-economy integration on carbon-emission intensity: theoretical model and empirical evidence. – Exploration of Economic Issues 12: 1-16.
[3] Chen, Y., Hu, W. (2011): Price distortion, factor misallocation, and efficiency loss: theory and evidence. – Economic Quarterly Journal 10: 1401-1422.

[4] Crippa, M., Guizzardi, D., Pagani, F., Schiavina, M., Melchiorri, M., Pisoni, E., Graziosi, F., Muntean, M., Maes, J., Dijkstra, L., Van Damme, M. (2023): Insights on the spatial distribution of global, national and sub-national GHG emissions in EDGAR v8.0. – Earth System Science Data Discussions 1-28. https://edgar.jrc.ec.europa.eu/dataset_ghg2025#p2.

[5] Freyaldenhoven, S., Hansen, C., Shapiro, J. M. (2019): Pre-event trends in the panel event-study design. – American Economic Review 109: 3307-3338. https://www.sci-hub.vg/10.1257/aer.20180609.

[6] Gardner, J. (2022): Two-stage differences in differences. – arXiv preprint 2207.05943. https://doi.org/10.48550/arXiv.2207.05943.

[7] Ge, L., Mo, L., Huang, N. (2022): Digital-economy development, industrial-structure upgrading, and urban carbon emissions. – Modern Finance 10: 20-37.

[8] Guo, P., Wang, G. (2023): The synergistic pollution-reduction and carbon-reduction effect and mechanism of the digital economy: empirical evidence from prefecture-level cities. – Resources Science 45: 2117-2129.

[9] He, W., Wen, J., Zhang, M. (2022): The impact of digital-economy development on China’s green ecological efficiency: evidence from a two-way fixed-effects model. – Economic Issues 1: 1-8.

[10] Huang, J., Liu, Q., Cai, X., Zhao, B. (2018): The effect of technological factors on China’s carbon intensity: new evidence from a panel threshold model. – Energy Policy 115: 32-42. https://doi.org/10.1016/j.enpol.2017.12.008.

[11] Huang, Q., Yu, Y., Zhang, S. (2019): Internet development and manufacturing productivity improvement: mechanisms and Chinese evidence. – China Industrial Economics 8: 5-23.

[12] Jiang, H., Deng, F. (2025): Synergistic governance effect of new-energy demonstration-city construction on pollution and carbon reduction. – Soft Science 7: 60-69.

[13] Jiang, T. (2022): Mediation and moderation effects in causal-inference empirical research. – China Industrial Economics 5: 100-120. 10.19581/j.cnki.ciejournal.2022.05.005.

[14] Kong, D., Lin, C., Wei, L., Zhang, J. (2022): Information accessibility and corporate innovation. – Management Science 68: 7837-7860. https://doi.org/10.1287/mnsc.2021.4224.

[15] Kou, J., Xu, X. (2025): Energy-saving and emission-reduction effects of the digital economy: a dual-control and pollution-reduction perspective. – Industrial Economics Research 2: 15-28.

[16] Li, C., Yan, X., Song, M., Liu, Y. (2020): FinTech and corporate innovation: evidence from NEEQ-listed firms. – China Industrial Economics 1: 81-98.

[17] Li, G., Zhou, X. (2021): Can promoting the digital economy improve China’s environmental pollution? Evidence from the Broadband China strategy. – Macroeconomic Research 7: 146-160.

[18] Li, Q., Wen, J. (2025): Does the low-carbon city pilot promote synergistic pollution and carbon reduction? – Journal of Dalian University of Technology 46: 40-50.

[19] Liao, Z. Z., Ru, S. F. (2024): The impact of digital technological innovation on urban energy structure optimization in China: a perspective based on biased technological progress. – Resources Science 46: 1881-1892.

[20] National Engineering Laboratory for Big Data Circulation and Trading Technology & Shanghai Data Exchange (2024): 2024 China data transaction market research and analysis report. – Shanghai Data Exchange. https://max.book118.com/html/2025/0423/6155112032011114.shtm.

[21] Shi, D. (2022): Evolution of industrial-development trends under the digital economy. – China Industrial Economics 11: 26-42. 10.19581/j.cnki.ciejournal.2022.11.001.

[22] Shi, Y., Wang, X., Qin, F., Liu, L. (2024): The utility of the market-oriented allocation of data factors for building a national unified market. – Science Research Management 45: 1-10.

[23] Song, D., Zhu, W., Ding, H. (2022): Does enterprise digitalization promote green technological innovation? Evidence from heavily polluting listed firms. – Finance & Economics Research 4: 34-48.
[24] Song, W., Cao, W., Zhou, Y. (2023): Data-factor empowerment, R&D decisions, and innovation performance: evidence from Chinese manufacturing. – Management Review 35: 112-121.
[25] Su, J., Zhao, C., Wang, B. (2022): Can data-factor agglomeration realize coordinated regional development? On agglomeration and coordination in a large country. – Journal of Finance and Economics 6: 62-77.
[26] Sun, L., Abraham, S. (2021): Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. – Journal of Econometrics 225: 175-199. https://doi.org/10.1016/j.jeconom.2020.09.006.
[27] Sun, Y., Yang, M. (2020): Club convergence and the source of regional disparities in China's green total factor productivity. – Journal of Quantitative & Technical Economics 37: 47-69.
[28] Tao, C., Ding, Y. (2022): Why can data factors become an innovation dividend? Evidence from human-capital matching. – China Soft Science 5: 45-56.
[29] Tian, X., Li, R. (2022): Digital-technology empowerment of the transformation and development of the real economy: an analytical framework based on Schumpeterian endogenous-growth theory. – Management World 5: 56-74.
[30] Wang, X., Li, J. (2022): Does the digital economy effectively promote energy conservation and carbon reduction? – China Population, Resources and Environment 32: 83-95.
[31] Wang, Y., Zhang, Y., Li, J. (2022): Digital finance and carbon emissions: evidence from micro data and machine-learning models. – China Population, Resources and Environment 32: 1-11.
[32] Wang, Z., Chu, E. (2023): Can information-infrastructure construction achieve both emission reduction and efficiency gains? A green-innovation perspective. – Modern Finance 43: 74-89.
[33] Xie, K., Xia, Z., Xiao, J. (2020): How big data becomes a real production factor: a product-innovation perspective. – China Industrial Economics 5: 42-60.
[34] Xu, X., Ren, X., Chang, Z. (2019): Big data and green development. – China Industrial Economics 4: 5-22.
[35] Xu, X., Zhao, M., Li, T., Chen, L. (2023): Data factors and enterprise innovation: a perspective based on R&D competition. – Economic Research 58: 39-56.
[36] Yang, B. (2025): Data element marketization and energy efficiency of heavy polluting enterprises: a technology innovation perspective. – Journal of Environmental Management 391: 126318. https://doi.org/10.1016/j.jenvman.2025.126318.
[37] Yang, G., Wang, H., Fan, H., Liu, Q. (2023): The carbon-reduction effect of the digital economy: theoretical analysis and empirical evidence. – China Industrial Economics 5: 80-98.
[38] Yu, C., Shen, B. (2024): The impact of digital-economy development on factor-market distortions in China. – Science Research Management 45: 62-71.
[39] Yuan, H., Zhu, C. (2018): Have national high-tech zones facilitated China's industrial-structure transformation and upgrading? – China Industrial Economics 8: 60-77.
[40] Zhan, Y., Huang, J., Yi, Y., Wu, F. (2025): Data elements marketization and enterprise digital transformation. – Economic Analysis and Policy. https://doi.org/10.1016/j.eap.2025.10.011.
[41] Zhao, F., Xu, Y., Zhu, M., Zhang, T. (2024): How does the market-oriented allocation of data factors influence ESG responsibility fulfilment in state-owned enterprises? Evidence from a quasi-natural experiment. – China Soft Science 10: 212-224.
[42] Zhao, Y., Fan, S., Niu, R. (2025): The impact of market-oriented data-factor development on urban total factor productivity. – Modern Finance 8: 23-40.

[43] Zheng, G., Zhang, X., Zhao, X. (2024): Can the market-oriented allocation of data factors promote enterprise green innovation? Evidence from a quasi-natural experiment of urban data trading platforms. – Journal of Shanghai University of Finance and Economics 3: 33-48.

[44] Zhu, X., Wei, W., Wang, J. (2024): Data factors, new-type infrastructure, and the path of industrial-structure adjustment. – Southern Economy 1: 107-123.

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