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The Impact of Data Element Marketization on Green Total Factor Energy Efficiency: Empirical Evidence from China

Ying Peng [1,2], Xinyue Wang [1] and Weilong Gao [3,*]

[1] School of Economics and Management, Changchun University of Technology, Changchun 130012, China; pengying@ccut.edu.cn (Y.P.); 20233416@stu.ccut.edu.cn (X.W.)
[2] Collaborative Innovation Center for Green and Low Carbon Development, Changchun University of Technology, Changchun 130012, China
[3] Institute of National Development and Security Studies, Jilin University, Changchun 130012, China
* Correspondence: gaoweiling@jlu.edu.cn

Abstract: Given the escalating severity of climate change and environmental degradation, the transition to green and low-carbon energy has become a strategic priority for China's economic development. Green total factor energy efficiency (GTFEE), which captures energy utilization efficiency while accounting for environmental constraints and desirable outputs, has emerged as a key indicator for evaluating green energy transition performance. Data element marketization (DEM), as a vital institutional innovation, provides new impetus for accelerating the transition to green and low-carbon energy. This study leveraged the establishment of China's data trading platforms as a quasi-natural experiment to systematically assess the effects, mechanisms, and spatial heterogeneity of DEM on urban GTFEE. The findings reveal that DEM has a statistically significant positive impact on urban GTFEE in the short term, while demonstrating a gradual diminishing marginal effect over the long term. Furthermore, this study uncovered heterogeneous effects based on factors such as city type, urban energy intensity, and new-energy pilot, as well as urban government governance capacity. Mechanism analysis demonstrated that DEM enhances urban GTFEE by accelerating the generation of data elements and fostering their deep integration with artificial intelligence (AI). Spatial analysis indicated that, while DEM significantly improves GTFEE in local cities, it generates negative spillover effects on neighboring cities due to the persistence of the digital divide.

Keywords: data element marketization; green total factor energy efficiency; data elements; artificial intelligence; digital divide

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1. Introduction

As a cornerstone of China's modernization and development, the clean, low-carbon, and efficient use of energy is not only fundamental to sustainable economic growth but also a strategic pillar in addressing global climate change and environmental pollution [1]. Table 1 illustrates the structure of energy consumption in China from 2009 to 2024. In 2024, China's energy consumption structure underwent a significant transformation, with total energy consumption reaching 5.96 billion metric tons of standard coal equivalent (SCE), reflecting a year-on-year increase of 4.3%. Further, crude oil consumption decreased by 1.2%, and natural gas consumption increased by 7.3% [2]. The total supply of non-fossil energy has increased to 1.18 billion tons of SCE, and China has made substantial progress in renewable energy generation, including wind and solar power, marking a critical breakthrough in its green and low-carbon transformation [3]. However, despite

the growing share of renewable energy in China's overall energy consumption, fossil fuels continue to dominate, exerting increasing pressure on the environment. The Outline of the 14th Five-Year Plan (2021–2025) for National Economic and Social Development and Vision 2035 of the People's Republic of China explicitly emphasizes the promotion of the energy consumption revolution and the green low-carbon transition. The challenge of sustaining economic growth while reducing reliance on traditional fossil energy has become a central issue in China's current green energy transition [4].

Table 1. China's energy consumption structure from 2009 to 2024.

Year	Energy Consumption Total (10,000 Tons of SCE)	Proportion of Coal in Total Energy Consumption (%)	Proportion of Petroleum in Total Energy Consumption (%)	Proportion of Natural Gas in Total Energy Consumption (%)
2009	336,126	71.6	16.4	3.5
2010	360,648	69.2	17.4	4
2011	387,043	70.2	16.8	4.6
2012	402,138	68.5	17	4.8
2013	416,913	67.4	17.1	5.3
2014	428,334	65.8	17.3	5.6
2015	434,113	63.8	18.4	5.8
2016	441,492	62.2	18.7	6.1
2017	455,827	60.6	18.9	6.9
2018	471,925	59	18.9	7.6
2019	487,488	57.7	19	8
2020	498,314	56.9	18.8	8.4
2021	525,896	55.9	18.6	8.8
2022	540,956	56	18	8.4
2023	572,000	55.3	18.3	8.5
2024	596,000	53.2	17.4	8.8

Note: The proportions of petroleum and natural gas in total energy consumption in 2024 were calculated based on data from the 2024 Statistical Communiqué of the National Bureau of Statistics of China.

The escalating impacts of climate change, which are exacerbated by carbon emissions from fossil fuel, necessitate a re-evaluation of conventional energy efficiency metrics. GTFEE integrates energy consumption, economic growth, and environmental pollution into a unified framework, enabling the systematic quantification of synergies in the energy–economy–environment nexus. GTFEE represents a multidimensional efficiency paradigm that integrates economic growth with sustainable development by improving energy efficiency, reducing environmental pollution, and lowering carbon emissions. As a key metric, GTFEE critically assesses the coordination of energy utilization efficiency, ecological preservation, and economic expansion [5]. Key factors influencing GTFEE include policy-driven initiatives, technological innovation, and the optimization of industrial structures. Low-carbon and environmental policies, along with the effectiveness of their implementation, are crucial in enhancing GTFEE [6]. In particular, the pilot low-carbon city policy has significantly improved the GTFEE of cities by promoting green technological innovation and optimizing industrial structures [7]. Technological innovation, particularly breakthroughs in clean energy technologies, can effectively reduce carbon emissions and improve energy efficiency [8]. The transformation of high-energy-consuming, high-polluting industries into low-carbon and environmentally friendly sectors is also a significant strategy for promoting GTFEE improvement. In terms of mechanisms, external support factors, such as green finance and environmental regulation, have attracted increasing attention for their role in enhancing GTFEE [9]. Green finance policies provide financial support for the innovation of low-carbon technologies and green industries, facilitating green investment and financial flows for low-carbon projects [10]. Environmental regulations strengthen the control of

pollutant emissions, enforce energy efficiency standards, and improve the green energy utilization efficiency of enterprises [11].

Data elements are digital resources encoded in bits, characterized by non-rivalry, non-exclusivity, and increasing returns to scale, which challenge traditional concepts of production factors and progressively integrate into various sectors, including production, distribution, exchange, and consumption. Data element marketization (DEM), a central issue in the digital economy era, aims to optimize the circulation and utilization efficiency of data resources through market mechanisms, thereby catalyzing new drivers of socio-economic development [12]. Unlike conventional production factors, such as labor, capital, and land, data elements exhibit unique characteristics, including inherent replicability and infinite scalability, which generate multiplier effects through cumulative aggregation and cross-domain interactions [13]. At the macro level, this marketization process facilitates urban green transformation through two primary mechanisms: resource allocation optimization and industrial structure realignment [14]. At the micro level, DEM significantly enhances the innovative capabilities of enterprises, particularly those with a high degree of digitization [15]. As the value of data resources becomes increasingly apparent, data trading platforms have not only accelerated the process of data marketization but also provided new governance tools for enterprises and governments. In cross-regional and cross-industry data sharing and trading, these platforms effectively coordinate the interests of data suppliers and demanders, thereby unlocking the dividends of data elements [16].

DEM plays a pivotal role in driving regional economic transformation, fostering enterprise innovation, and advancing digital innovation [17]. Several studies confirm that the marketization of data elements facilitates the digital transformation of enterprises, using data trading platforms as quasi-natural experiments. This, in turn, provides crucial support for enhancing energy efficiency and driving green transformation [18]. This study focused on how DEM can be employed to improve green energy efficiency (GTFEE). Its main contributions are as follows:

(1) A multi-period difference-in-differences (DID) model was employed to examine both the short-term and long-term effects of DEM on enhancing urban GTFEE, based on the development of China's data trading platform as a quasi-natural experiment. Additionally, the heterogeneous effects of DEM on urban GTFEE were comprehensively analyzed from the perspectives of city type, urban energy intensity, the new-energy pilot policy, and urban governance capacity.
(2) This study explored the mechanisms by which DEM influences urban GTFEE through multiple pathways, including data elements, and the integration of data elements and AI. Furthermore, it reveals how DEM can enhance urban GTFEE by fostering the integration of data elements and AI.
(3) Spatial econometric models were applied within the frameworks of the economic distance matrix and economic geography nested matrix to investigate the potential digital divide arising from DEM. By revealing the spatial heterogeneity of the effects of differences in digital infrastructure and economic development on the policy of DEM, this study provides a practical foundation for promoting balanced urban development and targeted policy implementation.

2. Theoretical Analysis

2.1. Background of the DEM Policy

The rapid advancement of information technology has positioned data assets as critical production factors that drive both social progress and economic growth [19]. The development of DEM has progressed through three stages: initial exploration, rapid

development, and maturity. The policy history of DEM development in China is shown in Figure 1.

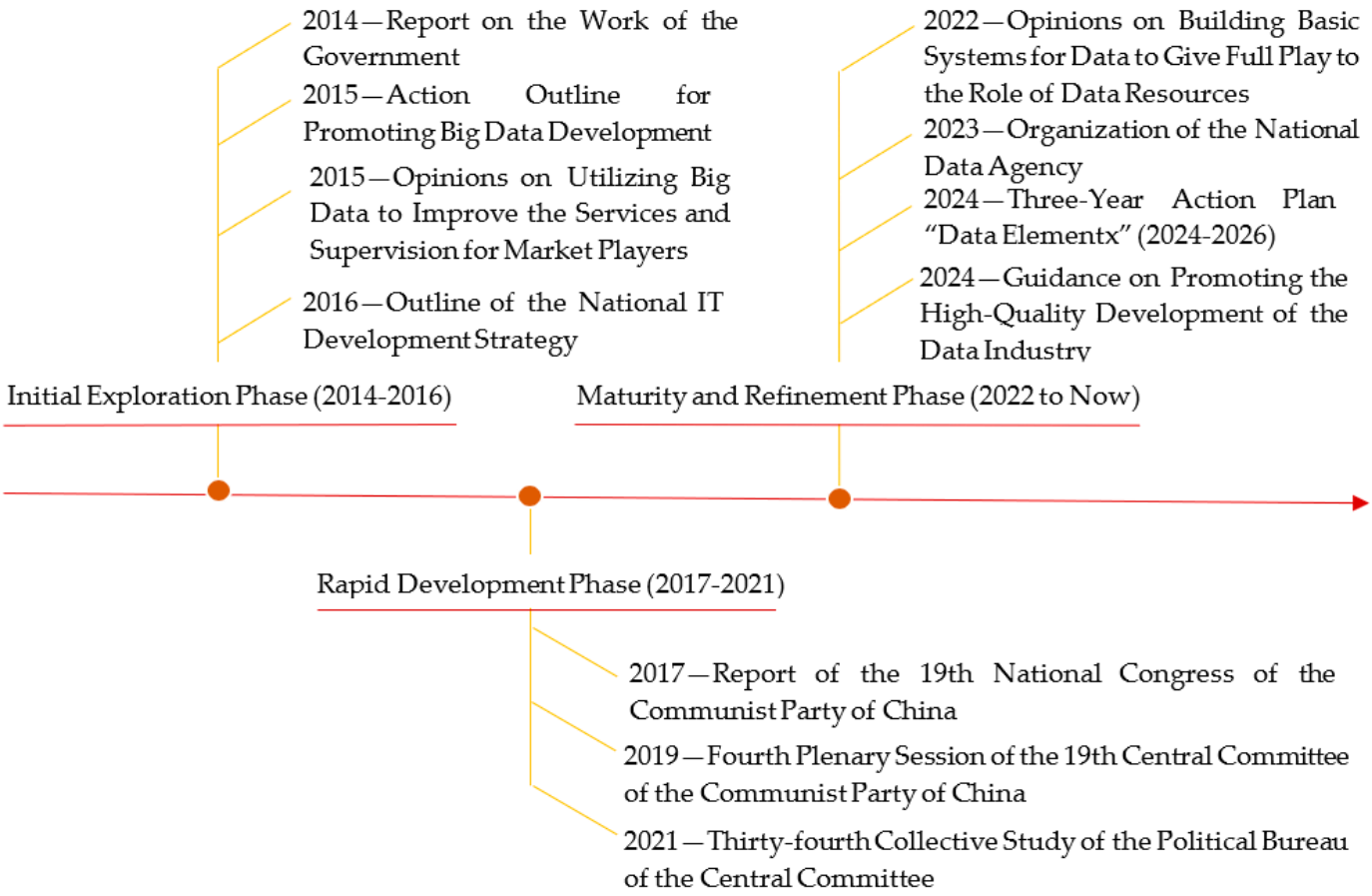


Figure 1. Policy history of the development of DEM in China.

In the initial exploration phase (2014–2016), the government first introduced the concept of DEM. In 2016, the Ministry of Industry and Information Technology released the "Big Data Industry Development Plan" (2016–2020), which proposed enabling online trading and resource integration of data elements through establishing data trading platforms, thereby promoting the rationalization and allocation of data elements. Meanwhile, Guiyang, Jiangsu, and Hangzhou established 12 big data trading platforms, marking the early advancement of DEM.

During the rapid development phase (2017–2021), policies transitioned from theory to practice. Data elements were formally recognized as a new type of production factor, and the construction of a foundational institutional framework began. The "Report of the 19th CPC National Congress" and the "4th Plenary Session of the 19th Central Committee of the CPC" clearly highlighted the critical role of data elements in economic development and promoted the deep integration of the digital economy with the real economy. However, the development of data trading platforms has been constrained by lagging institutional mechanisms, as well as insufficient laws and regulations. Consequently, the number of new platforms has decreased, although the overall marketization process has not stalled.

In 2022, DEM entered a stage of maturity, with continuous improvements to the policy system, focusing on the standardization and high-quality development of the data element market. In 2024, the "Guiding Opinions on Promoting the High-Quality Development of the Data Industry" and the "Data Element×" Three-Year Action Plan (2024–2026), along with other policy documents, were released. These measures further accelerated the devel-

opment of an improved institutional mechanism for DEM, activated the potential of data elements, and marked the entry of DEM into a new stage. As of now, China's data trading platform has expanded to 13 provinces and municipalities, including Beijing, Tianjin, Guizhou, Hubei, and Guangxi, forming a relatively extensive data element market network.

2.2. Research Hypotheses

DEM gradually facilitates the improvement of urban GTFEE through the distinctive characteristics of data elements, namely, their reusability, synergy, and scalability.

First, the reusability of data elements is crucial in mitigating information asymmetry and reducing technological innovation costs. The reusability of data elements bridges information gaps, enhances the accuracy of energy demand forecasting, optimizes energy utilization, and ensures precise green energy management [20]. For example, Shenzhen's smart energy platform integrated data on industrial energy consumption, power grids, and environmental monitoring to form an Energy Big Data Platform. Through this platform, real-time data supported the trading of energy-saving quotas, which helped enterprises optimize energy use based on predictive algorithms. Furthermore, the repeated utilization of existing data on energy consumption, environmental monitoring, and traffic flow reduces research-and-development costs for technological innovation while minimizing the inputs required for management optimization [21].

Second, the synergistic nature of data elements fosters deep cross-industry and cross-sector integration, serving as a key driver for improving urban GTFEE [22]. By integrating multidimensional data such as energy consumption, weather patterns, and traffic flow, intelligent algorithms enable optimized energy scheduling, thereby enhancing the efficiency of green energy utilization [23]. The synergy of data elements strengthens interactions among diverse production factors, advances energy management optimization from sector-specific to cross-sector applications, and deepens both the breadth and depth of green energy utilization [24].

Third, the scalability of data elements overcomes traditional constraints on the supply of production factors, introducing a new paradigm of increasing returns to scale for GTFEE improvement [25]. Large-scale data integration and analysis allow cities to monitor energy system operations in real time, detect inefficiencies in energy consumption, and optimize energy allocation with greater precision through data-driven insights [26]. The scalability of data facilitates the digital transformation of the energy industry and infrastructure and further advances the green and low-carbon transition of the economy and society [27]. DEM's impact on GTFEE is multidimensional, overcoming traditional supply constraints on production factors through the reusability, synergy, and scalability of data elements, thereby fostering the green transformation of the entire energy utilization and management process [28].

H1. DEM can significantly improve the urban GTFEE.

DEM accelerates the development of data elements by establishing efficient data circulation channels, rational market mechanisms, standardized application frameworks, and robust security assurance systems, thereby transforming data from a mere production factor into a key driver of economic growth and technological innovation [29]. Data elements' impact on GTFEE primarily manifests through two channels: the economic growth effect and the industrial empowerment effect.

Regarding the economic growth effect, data elements generate a multiplier effect in value creation, significantly enhancing the productivity of traditional factors such as labor and capital, which in turn elevates GTFEE [30]. As an emerging production factor, data interact synergistically with conventional inputs, including labor and capital, while

their market-driven flow mechanism optimizes coordination and efficiency across energy production, transmission, and consumption processes, thereby improving green energy efficiency overall [31]. Additionally, energy demand forecasting and dynamic scheduling increasingly rely on data-driven methodologies to optimize all stages of energy production and consumption. This data-centric transformation facilitates the rapid deployment of green technologies, fosters the continuous expansion of green industries, and ultimately enhances GTFEE [32]. Regarding the industrial empowerment effect, the market-oriented operation of data elements lowers sectoral entry barriers while improving resource allocation efficiency in green industries. This transformation reduces production costs for sustainable goods and stimulates the growth of green sectors [33]. Furthermore, data elements strengthen synergies across various stages of the industrial chain, enabling enterprises to reduce operational costs, enhance industry-wide competitiveness, and ultimately foster a fully integrated green industrial ecosystem [34].

H2a. DEM improves the city's GTFEE by accelerating the data element development process.

The evolution of next-generation AI reflects a deep integration between theoretical logic capabilities and data-driven insights, characterized by continuous iteration and progressive advances [35]. With ongoing developments in deep neural networks, machine learning, and other theoretical models, alongside improvements in multimodal data processing capabilities, data-driven enhancement has enabled AI models to exhibit the potential for "intelligent emergence". The interaction between data insights and theoretical logic remains the core driving force behind AI development [36]. Data serve as the foundation for AI development, and high-quality and large-scale data application provides essential support for green energy technology innovation [37]. By leveraging high-quality datasets and AI's deep learning capabilities, energy management systems can comprehensively analyze energy usage patterns and implement refined management of energy production and consumption through intelligent scheduling, thereby improving overall green energy utilization efficiency [38]. Furthermore, the application of AI in enhancing GTFEE is contingent upon computational power. With continuous improvements in computing capabilities and the efficient execution of data network scheduling, energy enterprises can extract valuable insights from vast amounts of real-time data, enabling them to formulate optimal energy management strategies that enhance the efficiency of green energy projects [39]. The optimal scheduling of computational resources further supports the refined management of large-scale green energy projects, improving overall efficiency and resource utilization [40]. Therefore, the deep integration of data elements and AI not only advances GTFEE but also accelerates green technology innovation and application.

H2b. DEM improves urban GTFEE by facilitating the deep integration of data elements with AI.

The digital divide in the spatial effects of GTFEE must not be overlooked during the development of pilot data trading platforms [41]. Disparities in digital infrastructure between developed and less developed regions, particularly in terms of data resources, significantly constrain the capacity of resource-scarce regions to access, process, and apply green energy technologies. This disparity leads to a lag in GTFEE improvement in less developed regions [42]. Moreover, variations in data accessibility and utilization capabilities enable developed regions to leverage high-quality datasets for energy management optimization, whereas less developed regions face technological and capacity constraints that hinder their ability to advance innovations in green energy management [43]. Additionally, disparities in platform access and market regulations create further challenges. High entry costs and

complex market mechanisms limit the participation of less developed regions in DEM [44]. Furthermore, differences in green technology innovation and industrial empowerment allow developed regions to dominate in the application and promotion of green technologies, exacerbating the challenges faced by less developed regions in improving GTFEE [45]. As a result, the spatial effects of the digital divide within DEM constrain the potential for GTFEE improvement in less developed regions, thereby intensifying interregional disparities in green development.

H3. There is spatial heterogeneity in the impact of DEM on urban GTFEE, which is influenced by the digital divide phenomenon.

The research framework diagram illustrating the effect of DEM on GTFEE is illustrated in Figure 2.

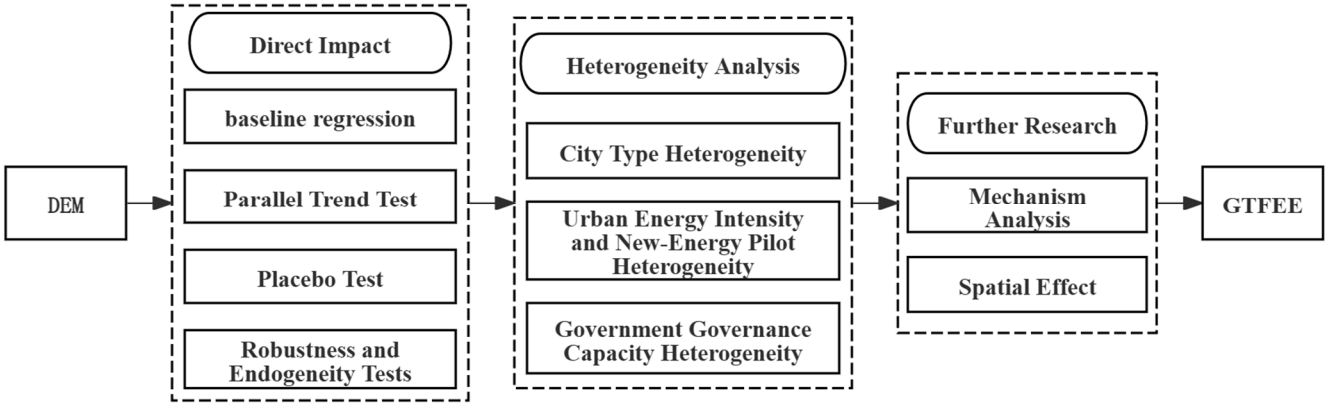


Figure 2. Research framework diagram of the effect of DEM on GTFEE.

3. Models and Variables

3.1. Model

To examine the direct impact of DEM on urban GTFEE, the multi-period DID model was specified as follows:

$$GTFEE_{it} = a_0 + \alpha_1 DEM_{it} + \alpha_2 X_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (1)$$

where $GTFEE_{it}$ is the city's GTFEE, which represents the GTFEE of city t in year i, and DEM_{it} is a dummy variable indicating the implementation of DEM. i represents the city. The coefficient α_1 measures the extent to which DEM influences the city's GTFEE. X_{it} denotes a set of control variables, while μ_i and ν_t represent individual fixed effects and time-fixed effects, respectively. ε_{it} is the random error component.

3.2. Variables

3.2.1. Dependent Variable

Synergizing the policy objectives of carbon reduction, pollution reduction, greening, and growth requires careful attention to the multidimensional and integrated effects of greening the economy and society in terms of GTFEE. This involves ensuring the interaction and balanced development among various policy measures [46]. The Urban GTFEE Indicator System systematically evaluates the multiple effects of the green transition in the economic, environmental, and social domains.

It does so by integrating input indicators, desired outputs, and undesired outputs at three distinct levels [47]. The input indicators encompass critical elements such as labor,

capital, energy, and land. These indicators reflect the level of resource inputs required to achieve GTFEE and help identify inefficiencies and opportunities for optimization in resource allocation during the energy transition process (Table 2). Desired outputs include both economic and ecological outputs, aiming to measure the dual objectives of economic growth and ecological improvement. Conversely, undesired outputs capture negative externalities, such as environmental pollution and carbon emissions, thus allowing for the identification of potential adverse impacts from the transition process. The system not only focuses on the efficiency of resource inputs but also quantitatively monitors the dual goals of economic growth and ecological enhancement, while effectively tracking possible negative impacts. This provides a scientific basis and policy support for the synergistic advancement of GTFEE.

Table 2. Evaluation indicators for GTFEE in cities.

Type of Indicator	Indicators	Measurement Indicators	Unit
Input	Labor	Number of employees in the unit at the end of the year	Ten thousand people
	Capital	Fixed capital stock	Ten thousand dollars
	Energy	Total energy consumption	Billion tons of standard coal
	Land	Built-up area	Square kilometers
Desired output	Economic benefits	Real GDP (real GDP at constant 2008 prices)	Ten thousand dollars
	Ecological benefits	Green area of parks	Hectares
Undesired output	Environmental pollution	Composite index of industrial wastewater emissions, sulfur dioxide emissions, and dust and fume emissions	-
	Carbon emission	Carbon dioxide emissions	Ten thousand tons

A super-efficient SBM model that includes undesired outputs is chosen to measure the GTFEE of the cities [48]. Suppose that the kth decision unit $(k = 1, 2, \ldots n)$ has an input vector $x \in R_+^m$, a desired output vector $y^g \in R_+^{s1}$, and an undesired output vector $y^b \in R_+^{s2}$, and define the matrices $X = [x_1, x_2, \ldots x_n] \in R_+^m \times n$, $Y^g = \left[y^{g1}, y^{g2}, \ldots y^{gn}\right] \in R_+^{s1} \times n$, and $Y^b = \left[y^{b1}, y^{b2}, \ldots y^{bn}\right] \in R_+^{s2} \times n$.

For decision unit k, the measurement formula is as follows:

$$\begin{aligned} \min\rho = & \frac{1+\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1-\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}s_r^g/y_{rk}^g+\sum_{t=1}^{s_2}s_t^b/y_{tk}^b\right)} \\ \text{s.t.} & \sum_{j=1,j\neq k}^{n} x_{ij}\lambda_j - s_i^- \leq x_{ik} \\ & \sum_{j=1,j\neq k}^{n} y_{rj}\lambda_j + s_r^g \geq y_{rk}^g \\ & \sum_{j=1,j\neq k}^{n} y_{tj}\lambda_j - s_t^b \leq y_{tk}^b \\ & \lambda \geq 0, s^g \geq 0, s^b \geq 0, s^- \geq 0 \end{aligned} \tag{2}$$

where λ is a vector of weights and s^g, s^b, and s^- are slack variables. $\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}$ is the average degree of inefficiency of inputs, and $\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}s_r^g/y_{rk}^g+\sum_{t=1}^{s_2}s_t^b/y_{tk}^b\right)$ is the average degree of inefficiency of outputs.

3.2.2. Independent Variable

Table 3 presents the cities where data trading platforms have been built, including the years they were first implemented. Since the establishment, in 2014, of China's first data trading platform, the Zhongguancun Digital Sea Big Data Trading Service Platform, numerous cities across the country have followed suit, setting up their own data trading platforms. These platforms are located across economically developed regions, such as Beijing, Shanghai, Guangzhou, and Shenzhen, as well as central regions, including Wuhan, Xi'an, and Chongqing. They also extend to western regions, such as Lanzhou and Urumqi.

Table 3. Cities that have established data trading platforms and year established.

City	Year Established	City	Year Established
Beijing	2014	Urumqi	2016
Guiyang	2015	Qingdao	2017
Hangzhou	2015	Xinxiang	2017
Shenzhen	2015	Zhengzhou	2017
Shijiazhuang	2015	Changchun	2018
Wuhan	2015	Hefei	2020
Xianyang	2015	Jinan	2020
Yancheng	2015	Nanning	2020
Chongqing	2015	Taiyuan	2020
Guangzhou	2016	Deyang	2021
Harbin	2016	Foshan	2021
Lanzhou	2016	Haikou	2021
Shanghai	2016	Suzhou	2021

Note: The statistical period for China's data trading platforms is 2014–2021.

This study employed a difference-in-differences (DID) research design to evaluate the impact of data trading platforms. Cities that implemented these platforms constituted the treatment group (treat = 1), while comparable cities without such platforms served as the control group (treat = 0). We constructed a time indicator variable (post) that equals 1 for the implementation year and all subsequent years or 0 otherwise. The causal effect of DEM was then estimated using the interaction term (treat × post), which captures the policy's differential impact on treatment versus control cities.

3.2.3. Mechanism Variable

The mechanism variables include data elements, and the integration of data elements and AI. Table 4 reports the evaluation index for data elements and AI. Based on the life cycle of data elements, an evaluation index system was constructed across three dimensions: data element generation and acquisition, data element processing and sharing, and data element application and benefits [49]. The generation and acquisition dimension focuses on the source, quality, and collection efficiency of data. The processing and sharing dimension assesses the capability and security of data cleaning, storage, analysis, and sharing. The application and benefit dimension measures both the breadth and depth of data application, as well as the economic and social benefits it generates, aiming to comprehensively evaluate the realization of data elements' value in each segment. The level of AI application is represented by the combination of robot installation density and the number of AI enterprises.

Table 4. Evaluation index for data elements and AI.

Indicators	Type of Indicator	Measurement Indicators	Unit
Data Elements	Data element generation and access	Internet users per 100 population	Households/ 100 persons
		Cell phone subscribers per 100 population	Households/100 persons
		Total telecommunication services per capita	Ten thousand Chinese yuan/person
	Data element processing and sharing	Percentage of employees in computer services and software	%
		Telecommunications revenue per capita	Ten thousand Chinese yuan/person
	Data element applications and benefits	Level of utilization of data elements	-
		Digital Inclusive Finance Index	-
AI	Technology foundation and support	Robot mounting density	Unit
	Technology practice and application	Number of AI companies	Pieces

The entropy value method was employed to measure the level of data elements and AI, while the modified coupling coordination degree model was used to assess the degree of integration between data elements and AI.

3.2.4. Control Variable

We selected the following control variables that influence the GTFEE of cities:

(1) Financial development (FD): this is measured by the ratio of the year-end deposit and loan balances of financial institutions to the city's gross regional product.
(2) Openness (OPEN): the degree of openness is indicated by the ratio of the total value of imports and exports of goods to the city's GDP.
(3) Government intervention (GI): this is characterized by the proportion of local government expenditure from the general budget relative to regional GDP.
(4) Industrialization (IND): the level of industrialization is measured by the ratio of the value added by the secondary industry to regional GDP.
(5) Infrastructure (INF): the development of urban infrastructure is reflected by the logarithm of urban road area per capita.
(6) Environmental regulation (ER): the intensity of urban environmental regulation is determined according to the logarithm of investment in environmental pollution control.

3.3. Data Sources

Data on robot installation density were sourced from the IFR Robot Database, while data on data element utilization were obtained from the annual reports of listed companies. Government governance data were derived from official government work reports. Additional data were drawn from the China Urban Statistical Yearbook (2010–2022), China Financial Statistical Yearbook (2010–2022), and China Environmental Statistical Yearbook (2010–2022), as well as from the China Research Data Service Platform and the State Intellectual Property Office. To address missing data, linear interpolation was employed, allowing for the creation of a panel dataset for 275 prefecture-level cities in China, spanning from 2009 to 2021. The descriptive statistics of the key variables are presented in Table 5.

Table 5. Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
GTFEE	3575	0.228	0.179	0.014	1.311
DEM	3575	0.035	0.184	0.000	1.000
FD	3575	1.010	0.622	0.120	9.556
OPEN	3575	0.226	0.414	0.000	5.075
GI	3575	0.198	0.106	0.044	1.485
IND	3575	0.459	0.112	0.000	1.256
INF	3575	2.772	0.440	0.315	4.096
ER	3575	5.477	0.954	1.932	9.793
Data Elements	3575	0.145	0.062	0.014	0.554
Integration of Data Elements and AI	3575	0.152	0.072	0.026	0.608

4. Empirical Results

4.1. Baseline Results

Table 6 presents the regression results for the impact of DEM on urban GTFEE. Columns (1) and (2) show the results of fixed-effect regression with and without the control variables, respectively. In both cases, the regression coefficients were significantly positive at the 1% statistical level, indicating that DEM has a significant positive impact on urban GTFEE. Columns (3)–(5) show the regression results of GTFEE after lagging one, two, and three periods, respectively. The estimation results remained significantly positive, suggesting that DEM exerts a sustained effect on improving urban GTFEE. However, the regression coefficient gradually decreased as the lag period increased, indicating a diminishing long-term effect. These findings confirm that DEM positively impacts urban GTFEE in the short term. However, this positive effect gradually diminishes over time, with marginal returns weakening in the long term. Hypothesis 1 is verified.

Table 6. The baseline regression results.

Variable	GTFEE	GTFEE	L. GTFEE	L2. GTFEE	L3. GTFEE
	(1)	(2)	(3)	(4)	(5)
DEM	0.107 ***	0.091 ***	0.090 ***	0.085 ***	0.064 ***
	(6.36)	(5.43)	(5.59)	(5.59)	(5.41)
FD		0.036 ***	0.031 ***	0.011	0.006
		(3.10)	(2.99)	(1.19)	(0.78)
OPEN		−0.015	−0.004	0.008	0.028
		(−1.43)	(−0.24)	(0.33)	(1.03)
GI		−0.193 ***	−0.158 ***	−0.025	0.055
		(−3.95)	(−3.07)	(−0.37)	(0.90)
IND		0.168 **	0.060	−0.000	−0.114 **
		(2.32)	(0.87)	(−0.00)	(−2.12)
INF		−0.015	−0.023 **	−0.020 *	−0.013
		(−1.53)	(−2.41)	(−1.85)	(−1.36)

Table 6. *Cont.*

Variable	GTFEE	GTFEE	L. GTFEE	L2. GTFEE	L3. GTFEE
	(1)	(2)	(3)	(4)	(5)
ER		−0.008	−0.006	0.012 *	0.004
		(−1.35)	(−0.92)	(1.81)	(0.71)
City FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
N	3575	3575	3300	3025	2750
R^2	0.652	0.659	0.665	0.688	0.713

Note: The values of t are shown in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

4.2. Robustness Test

4.2.1. Parallel Trend Test

According to Table 3, the dummy year variable denotes the year in which the data trading platform for the city was established. Dummy variables were constructed for the four years before and after the establishment of the data trading platform, representing the year dummy variables for the four years preceding the implementation of the DEM policy, the implementation year, and the four years following its implementation. These variables were incorporated into the model to re-estimate the regression.

Figure 3 presents the results of the parallel trend test. The results indicate that, before the implementation of the DEM policy, the confidence interval of the regression coefficient included zero, suggesting no significant differences in the characteristics of GTFEE changes between the treatment and control groups. This finding supports the assumption of a parallel trend. However, after the implementation of the DEM policy, the confidence interval of the regression coefficient became significantly positive, demonstrating that DEM positively impacts urban GTFEE. These results confirm that DEM has a promotional effect, validating the reliability of the parallel trend test.

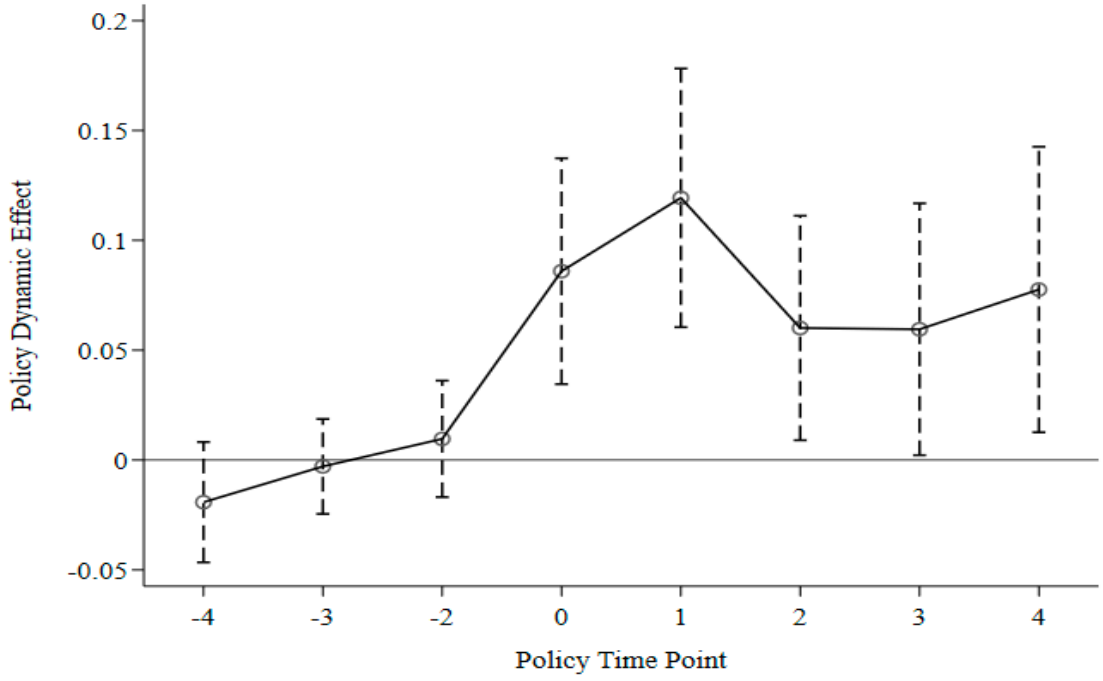


Figure 3. Parallel trend test results.

4.2.2. Placebo Test

A placebo test was conducted to assess whether the observed effect of DEM on urban GTFEE was influenced by random factors. In this test, 26 pilot cities for data trading platforms were randomly assigned, and the time of the establishment of these platforms was also randomly set. A total of 300 regression simulations were performed using the generated sample data. The results of the placebo test are shown in Figure 4. The mean values of the regression coefficients followed a normal distribution centered around zero, and most *p*-values exceeded the 0.1 threshold. These results indicate that the impact of DEM on urban GTFEE is not driven by stochastic factors, thereby confirming the robustness of the baseline regression results.

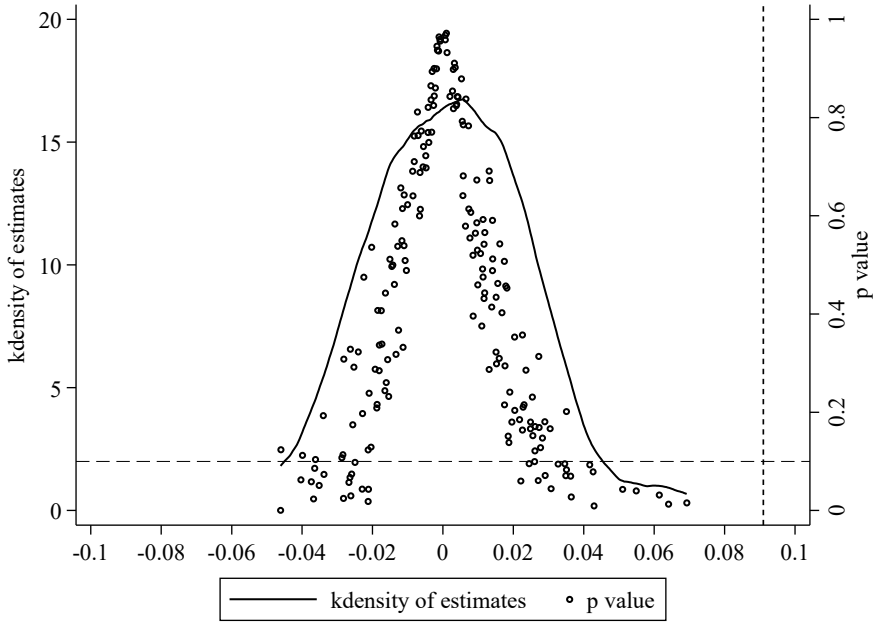


Figure 4. The placebo test results.

4.2.3. Robustness and Endogeneity Tests

Table 7 presents the results of the robustness tests. Column (1) displays the results of the Propensity Score Matching Difference-in-Differences (PSM-DID) test. To control for individual differences in the pilot policy, the PSM-DID method was used to regress the matched data. The regression coefficient was significantly positive, suggesting that the self-selection bias resulting from differences in initial characteristics can be controlled by matching the treatment group and the control group. This further validates the robustness of the research findings.

Table 7. Robustness test results.

Variable	GTFEE	GTFEE	GTFEE
	(1)	(2)	(3)
DEM	0.211 ** (2.45)	0.091 *** (5.43)	0.091 *** (5.28)
IV			
Controls	YES	YES	YES
City FE	YES	YES	YES
Year FE	YES	YES	YES
N	180	3575	3575
R^2	0.918	0.664	0.660

Note: The values of t are shown in parentheses. **, and *** indicate significance levels of 5%, and 1%, respectively.

Column (2) presents the results of the shrinkage treatment test. To mitigate the risk of "pseudo-regression" caused by outliers, regression was re-run after applying a 1% shrinkage treatment. The estimated coefficients remained significantly positive, indicating that the regression results were not influenced by extreme outliers, thus supporting the validity of the initial conclusions.

Column (3) shows the test results after excluding the impact of other policy shocks. To account for the potential interference of other relevant pilot policies during the observation period, we controlled for the national-level Big Data Comprehensive Experimental Zone, the Smart City Pilot Policy, and the Broadband China Pilot Policy, all of which are closely related to DEM. After controlling for policies, the regression coefficients remained significantly positive, further confirming the robustness of the research results.

Table 8 presents the results of the endogeneity test. To address potential endogeneity concerns, the instrumental variable (IV) approach, two-stage generalized method of moments (GMM) estimation, and machine learning techniques were employed.

Table 8. Endogeneity test results.

Variable	DEM	GTFEE	GTFEE	GTFEE
	(1)	(2)	(3)	(4)
DEM		0.075 ***	0.081 ***	0.114 ***
		(4.04)	(4.32)	(3.58)
IV	0.013 ***			
	(43.37)			
Controls	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	2532	2532	3025	3575
R^2		0.707	0.679	
Cragg–Donald Wald F statistic		1880.545		
Anderson canon. corr. LM statistic		1138.159		

Note: The values of t are shown in parentheses. *** indicates significance level of 1%.

A cross-term between the number of post offices per million people and the lagged period of the explanatory variable was constructed as an instrumental variable for DEM. This selection is justified by two key conditions: (1) the number of post offices reflects the level of regional communication infrastructure and information flow, satisfying the relevance condition of an instrumental variable, and (2) the number of post offices does not directly influence the current DEM, meeting the exogeneity condition. Columns (1) and (2) show the results of the first- and second-stage regressions using the instrumental variable approach. The instrumental variable successfully passed both the correlation test and the weak instrumental variable test. In the second stage, the estimated impact coefficient remained significantly positive, indicating that, even after mitigating endogeneity concerns, DEM continues to significantly contribute to urban GTFEE.

To further strengthen the reliability of the endogeneity test, two-stage GMM estimation and machine learning were applied to account for potential heteroskedasticity. The machine learning approach utilized cross-fitted Lasso regressions for both the outcome and treatment equations, with four-fold cross-fitting to mitigate overfitting and improve estimation accuracy. Columns (3) and (4) show the results of these robustness checks, showing that the estimated coefficients remained significantly positive, further supporting the reliability of this study's findings.

4.3. Heterogeneity Analysis

4.3.1. City Type Heterogeneity Tests

From the perspective of city type, the regression coefficient for diversified-industry cities was 0.101, which is statistically significant and positive, indicating that DEM exerts a significant positive effect on these cities. Diversified-industry cities typically exhibit a diversified industrial structure, with strengths in high-tech, service, and green industries. This industrial composition enables them to effectively leverage data elements to drive digital transformation and green technological innovation, thereby improving GTFEE. Conversely, the regression coefficient for resource-based cities was −0.094, which is statistically significant and negative, suggesting that DEM adversely impacts their GTFEE (see Table 9).

Table 9. Results of the city type heterogeneity test.

Variable	Diversified-Industry Cities	Resource Cities
	(1)	(2)
DEM	0.101 ***	−0.094 ***
	(5.78)	(−4.99)
Controls	YES	YES
City FE	YES	YES
Year FE	YES	YES
N	2171	1404
R^2	0.647	0.674

Note: The values of t are shown in parentheses. *** indicates significance level of 1%.

In resource-based cities, the negative impact of DEM on GTFEE stems from the combined effects of the energy rebound phenomenon and efficiency-oriented technological path dependence. On the one hand, Digital Economy Modeling (DEM) promotes the adoption of information technologies in energy-intensive industries, leading to improved energy utilization efficiency. However, the observed negative impact on resource-based cities substantiates the concerns about the "energy rebound effect" raised by Wang et al. [50]. The efficiency gains from implementing DEM reduce energy costs, which in turn incentivizes expanded production capacity. This expansion ultimately increases total energy consumption, thereby partially negating the initial benefits for energy conservation and emission reduction. On the other hand, DEM tends to prioritize improvements in the efficiency of traditional industries rather than encouraging green, alternative technological innovation. This path dependence steers technological progress away from green development objectives, deepens reliance on conventional energy sources, and reinforces high-carbon production capacities, thereby constraining the long-term improvement of GTFEE.

This conclusion provides empirical validation for the assertion of Yang et al. [51], who argue that the effects of digital transformation are strongly mediated by a city's industrial foundation and its capacity for green innovation.

4.3.2. Urban Energy Intensity and New-Energy Pilot Heterogeneity Tests

Table 10 presents the results of the heterogeneity analysis based on cities' urban energy intensity and new-energy pilot policies.

Table 10. Results of the test for heterogeneity in urban energy intensity and new-energy pilot cities.

Variable	Low-Energy-Intensity Cities	High-Energy-Intensity Cities	Non-New-Energy Pilot Cities	New-Energy Pilot Cities
	(1)	(2)	(3)	(4)
DEM	0.170 ***	0.044 ***	0.085 ***	0.138 **
	(4.62)	(3.34)	(4.58)	(2.46)
Controls	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	1768	1807	3087	488
R^2	0.587	0.760	0.646	0.779

Note: The values of t are shown in parentheses. **, and *** indicate significance levels of 5%, and 1%, respectively.

Energy intensity is defined as the ratio of total energy consumption to real GDP. In cities with low energy intensity, the estimated coefficient was 0.170 and statistically significant at the 1% level, indicating that DEM has a strong and positive impact on GTFEE. In contrast, although the coefficient in high-energy-intensity cities remained positive and statistically significant, its magnitude was considerably smaller. This disparity can be attributed to two primary factors. First, low-energy-intensity cities typically possess more advanced digital infrastructure and a higher capacity to absorb and apply new technologies, facilitating the effective integration of data elements into energy management and production systems. Second, the industrial structures of these cities are generally more aligned with data-driven energy efficiency improvements. Conversely, high-energy-intensity cities are often dominated by rigid, energy-intensive industries that limit the potential for digital transformation.

This heterogeneity is consistent with the findings of Wang and Zhong [52], who argue that digital infrastructure—due to its energy-intensive nature—may adversely affect urban energy efficiency. Their study highlights that the construction and operation of such infrastructure can increase energy demand and carbon intensity, particularly in cities that are heavily reliant on energy-intensive industries.

From the perspective of new-energy pilot cities, Columns (3) and (4) indicate that cities with a high level of green energy transition exhibited higher coefficients than those with a low level of transition, suggesting that the demand for and responsiveness to DEM vary across different stages of energy transition. In new-energy pilot cities, DEM significantly enhances green development efficiency by optimizing energy utilization and promoting sustainable innovation. Conversely, in non-new-energy pilot cities, the impact of DEM is relatively weak, as these cities are still in the initial phase of structural adjustment and policy adaptation. These findings are closely aligned with the conclusions drawn by Li and Zhang [53] in their evaluation of the Dual Pilot Policy.

4.3.3. Government Governance Capacity Heterogeneity Tests

To accurately assess the influence of government policy and interventions in digital governance and environmental energy governance, Python 3.11.5-based web-crawling technology was employed to statistically analyze keywords related to digital transformation and environmental energy governance in government reports. This approach enabled the quantification of government digital governance (GDG) and government environmental energy governance (GEEG) indicators. Based on the sample mean distribution of 275 cities from 2009 to 2021, the sample was divided into two groups (high and low) based on governments' governance capacity to examine the heterogeneous effects of DEM on urban GTFEE.

Table 11 presents the results of the heterogeneity test on government governance capacity. Regarding GDG, cities with a higher GDG capacity exhibited a regression coefficient of 0.117, which is significantly positive. This finding suggests that stronger government support in digital governance enhances data accessibility and utilization efficiency, thereby effectively promoting data-driven improvements in GTFEE. This result is consistent with the conclusions drawn by He et al. [54] in their research on how digital technology impacts environmental governance capacity in China. Their study emphasizes that advances in digital technology are intrinsically linked to the improvement of governance capacity, especially in areas such as environmental management, where effective data usage is crucial.

Table 11. Results of the test for heterogeneity in government governance capacity.

Variable	Low GDG	High GDG	Low GEEG	High GEEG
	(1)	(2)	(3)	(4)
DEM	0.009	0.117 ***	0.155 ***	0.033 *
	(0.30)	(5.94)	(5.86)	(1.84)
Controls	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	1677	1898	1768	1807
R^2	0.621	0.679	0.732	0.559

Note: The values of t are shown in parentheses. *, and *** indicate significance levels of 10%, and 1%, respectively.

Furthermore, in terms of GEEG, all regression coefficients remained significantly positive, indicating that strong environmental energy governance reinforces the positive impact of DEM on the green energy transition. However, in high-GEEG cities, the estimated impact coefficient was notably smaller. A closer examination revealed that high-GEEG cities are primarily located in old industrial bases and resource-dependent regions. These cities are characterized by industrial structures dominated by high energy consumption and high emissions and are constrained by traditional energy dependence and path-locking effects, making the implementation of green transformation considerably more challenging than in other regions. Such structural constraints hinder the deep integration of data elements and green technologies, thereby diminishing the effectiveness of DEM in enhancing GTFEE.

5. Further Research

5.1. Mechanism Analysis

To analyze the mechanism by which DEM impacts urban GTFEE, the following mechanism testing model was constructed:

$$M_{it} = \beta_0 + \beta_1 DEM_{it} + \beta_2 X_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (3)$$

where M_{it} represents the mechanism variable, including data elements, and the integration of data elements and AI. The regression results in Column (2) of Table 6 confirm the positive effect of DEM on GTFEE. Building on Model (3), the subsequent analysis investigated the pathway through which DEM influences GTFEE.

In Table 12, Column (1) examines the impact of data elements. The positive coefficient of DEM for data elements suggests that the DEM policy accelerates data element development. Furthermore, Bibri and Krogstie [55] provide evidence that data elements enhance GTFEE by improving energy management and minimizing waste. In their seminal study on environmental-data-driven smart sustainable cities, they argue that the integration of IoT and big data technologies into urban infrastructure facilitates real-time monitoring,

analysis, and decision-making related to energy flows and environmental performance. These findings offer strong support for the empirical validation of Hypothesis 2.

Table 12. Mechanism effect test results.

Variable	Data Elements	Integration of Data Elements and AI
	(1)	(2)
DEM	0.105 ***	0.073 ***
	(7.95)	(6.00)
Controls	YES	YES
City FE	YES	YES
Year FE	YES	YES
N	3575	3575
R^2	0.890	0.941

Note: The values of t are shown in parentheses. *** indicates significance level of 1%.

Column (2) evaluates the impact of the deeper integration of data elements with AI, and the results remain significantly positive. This indicates that DEM effectively facilitates the integration of data elements with AI. AI technology, by processing large-scale data, unlocks the potential for improved energy efficiency, while data elements provide the essential foundation for AI-driven data processing. The integration of data elements and AI fosters green technology innovation, supports industrial upgrading, and enhances GTFEE, which has been confirmed in the literature [56]. Hypothesis 3 is validated.

5.2. Spatial Effect

To account for the spatial interdependence of urban GTFEE, this study further examined the spatial effects of DEM on urban GTFEE. A spatial Durbin model (SDM) was constructed as follows:

$$GTFEE_{it} = \rho_1 W{\cdot}GTFEE_{it} + \vartheta_1 DEM_{it} + \vartheta_2 X_{it} + \delta_1 W{\cdot}DEM_{it} + \delta_2 W{\cdot}X_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (4)$$

where ρ_1 represents the spatial autoregressive coefficient of urban GTFEE, W is the weight matrix, ϑ_1 denotes the spatial regression coefficient of DEM, and δ_1 represents the spatial spillover effect of DEM.

To assess the spatial dependence of urban GTFEE, this study employed Global Moran's I index, which identifies and quantifies the spatial correlation of a given variable (Table 13). Under the economic–geographical nested matrix, the Global Moran's I values for urban GTFEE remained significantly positive from 2009 to 2021, indicating a strong and persistent positive spatial correlation in the study period. Given this observed spatial dependence, a spatial econometric model was applied to conduct an in-depth examination of the spatial effects of DEM on urban GTFEE, allowing for a more comprehensive understanding of how DEM influences GTFEE across different cities.

In Table 14, Columns (1) and (5) present the regression results of the spatial Durbin model under the economic distance matrix and economic geography nested matrix, respectively. The regression coefficients for DEM were positive at the 1% significance level, indicating that DEM significantly enhances the GTFEE of local cities. In contrast, the regression coefficients for the spatial lagged term were significantly negative, suggesting that DEM exerts a substantial negative spillover effect on the GTFEE of neighboring cities. Columns (2) to (4) and (6) to (8) illustrate the results of spatial effect decomposition. The regression coefficients for the direct effect were significantly positive, while those for the indirect effect were negative. Furthermore, the regression results for the total effect were statistically insignificant, reaffirming that DEM boosts local GTFEE but negatively impacts

the GTFEE of neighboring regions. The insignificant result for the total effect further underscores this conclusion. Hypothesis 4 is verified.

Table 13. Global Moran's index.

Year	Moran's I	Z-Value	*p*-Value	Year	Moran's I	Z-Value	*p*-Value
2009	0.030 ***	6.379	0.000	2016	0.025 ***	5.194	0.000
2010	0.030 ***	6.314	0.000	2017	0.035 ***	7.143	0.000
2011	0.037 ***	7.488	0.000	2018	0.013 ***	3.017	0.001
2012	0.031 ***	6.419	0.000	2019	0.018 ***	3.896	0.000
2013	0.026 ***	5.505	0.000	2020	0.030 ***	6.223	0.000
2014	0.013 ***	3.070	0.001	2021	0.030 ***	6.177	0.000
2015	0.021 ***	4.473	0.000				

Note: *** indicates significance level of 1%.

Table 14. Regression results of the spatial Durbin model.

Variable	Geographic Distance Matrix				Economic Distance Matrix			
	GTFEE	Direct	Indirect	Total	GTFEE	Direct	Indirect	Total
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DEM	0.094 ***	0.090 ***	−1.135 *	−1.045	0.100 ***	0.098 ***	−0.097 **	0.001
	(6.93)	(6.25)	(−1.67)	(−1.53)	(7.18)	(6.85)	(−2.07)	(0.02)
W * DEM	−0.375 **				−0.103 ***			
	(−2.29)				(−2.82)			
ρ	0.741 ***				0.243 ***			
	(15.55)				(7.76)			
Controls	YES	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	3575	3575	3575	3575	3575	3575	3575	3575
R^2	0.137	0.137	0.137	0.137	0.102	0.102	0.102	0.102

Note: The values of t are shown in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

While promoting local GTFEE, DEM has exacerbated the phenomenon of the digital divide, preventing neighboring cities from concurrently benefiting from the advantages of data marketization. (1) Infrastructure gaps: DEM primarily advantages cities with superior infrastructure. If neighboring cities possess weak digital infrastructure, they may struggle to effectively access and utilize data resources from local cities, directly hindering improvements in GTFEE within those neighboring areas. This finding resonates with the conclusions of Shirazi and Hajli [57], who emphasize that disparities in ICT infrastructure across regions create significant global digital divides, which in turn impede the diffusion of sustainable innovation. (2) The gap in technological innovation capacity: Data marketization creates new opportunities for local cities to drive innovation and advances in green technology; however, innovative resources and progress do not automatically diffuse to neighboring cities. These cities often fail to effectively adopt technology and draw on expertise from local cities, resulting in limited dissemination and application of green technology. (3) Limited policy spillover effects: local cities enhance GTFEE through policy support, yet the policy spillover effect remains weak, preventing neighboring cities from fully benefiting, which results in a lag in GTFEE improvement.

6. Research Summary and Outlook

6.1. Conclusions

This study considered the establishment of data trading platforms in China as an exogenous policy shock to systematically examine the impact of DEM on urban GTFEE. The key findings are as follows:

Firstly, the baseline regression revealed that DEM has a significant positive impact on urban GTFEE in the short term. However, this effect gradually weakens over time, with marginal returns diminishing in the long term. This temporal attenuation of the effectiveness of DEM is consistent with the findings of Dong et al. [58], who highlight that the positive impact of DEM development on urban green growth is primarily mediated through enhanced marketization, green technological innovation, and the expansion of digital inclusive finance. Although these channels can significantly accelerate green development in the early phases of DEM implementation, their marginal effects tend to diminish over time as the initial institutional, technological, and financial advantages are gradually exhausted.

From the perspective of city types, diversified-industry cities such as Suzhou and Guangzhou benefit significantly from DEM due to their advanced green manufacturing sectors and digital innovation capabilities. In contrast, resource-dependent cities such as Ordos or Jinchuan, being constrained by energy-intensive industries and path dependency, exhibit limited or even negative impacts on GTFEE. Moreover, the results align with those of Yu et al. [59], who point out that, in cities with rigid industrial structures, the digital economy may primarily serve to reinforce existing high carbon production capacities rather than stimulate alternative green innovation pathways. The negative coefficient of DEM in resource-based cities reflects this phenomenon of "technological lock-in", whereby digital tools optimize traditional industries but fail to redirect development toward low-carbon transitions.

Regarding energy intensity and new-energy pilot policies, DEM shows stronger positive effects in cities with lower energy efficiency but higher green transition intensity, such as Wuhan and Nanjing, where digital policies are closely aligned with ecological objectives. Moreover, DEM enhances government effectiveness by fostering synergy between digital governance and environmental energy governance, leading to amplified policy coordination and improved environmental outcomes, as illustrated in Shanghai's smart energy platform construction case. In regions with advanced digital development, DEM promotes technological innovation and industrial upgrading. In contrast, in regions with lower levels of digital development, the driving effects of DEM are relatively delayed [60].

Secondly, the mechanism analysis revealed that DEM optimizes resource allocation and fosters technological innovation by accelerating the development of data elements and promoting their deep integration with AI. Data elements enhance data mobility and accessibility, providing cities with more accurate decision-making support in energy management, reducing energy waste, and improving energy use efficiency. Data elements improve decision-making in energy use, as seen in Guangzhou, where AI-driven energy diagnostics reduced industrial waste heat emissions. This study also demonstrates that the integration of data elements with artificial intelligence (AI) plays a pivotal role in enhancing urban green total factor energy efficiency (GTFEE). By facilitating intelligent, data-driven decision-making in energy-intensive sectors, this synergy effectively reduces energy waste and mitigates adverse environmental externalities. These findings are consistent with those of Zhou et al. [61], who highlight AI's dual function in improving energy efficiency and advancing pollution control technologies. Collectively, the evidence confirms that the integration of data elements with AI serves as a catalyst for technological innovation and significantly promotes GTFEE.

Finally, the spatial effect analysis indicated that, while DEM significantly enhances GTFEE in local cities, it simultaneously produces adverse spatial spillover effects on neighboring cities, underscoring the spatial asymmetry in DEM's impact on GTFEE. This finding aligns with the conclusions of Jiao and Xia [62], who demonstrate that disparities in digital infrastructure and capabilities inhibit energy transition, particularly in regions that lag behind in digital innovation. Similarly, our results suggest that cities that employ DEM reap substantial benefits, while neighboring cities with weaker digital infrastructure may experience negative spillovers.

6.2. Policy Recommendations

Based on the above findings, the following policy recommendations are proposed to maximize the positive impact of DEM on enhancing urban GTFEE.

The development of DEM should be steadily advanced by expanding the coverage of pilot policies and refining institutional frameworks. Institutional improvements should prioritize four critical dimensions: clarifying data ownership, establishing dynamic pricing mechanisms, implementing standardized and secure trading protocols, and enhancing regulatory oversight to ensure market integrity and transparency. To promote effective implementation, eligible cities should be encouraged to launch scenario-specific pilot programs. For example, Hangzhou's "City Brain" initiative illustrates how digital governance systems can enhance energy efficiency through the real-time optimization of traffic flow and urban lighting. Similar applications should be adopted in other cities, such as industrial energy audits in Guangzhou, green supply chain traceability systems in Suzhou, and smart grid integration in Nanjing. Strengthening government–enterprise collaboration is essential to codeveloping digital platforms that support environmental monitoring, intelligent energy management, and broader synergies between DEM and GTFEE.

Narrowing the regional digital divide is critical to achieving spatial equity in the benefits derived from DEM. A "digital partnership assistance program" should be established to facilitate the transfer of digital infrastructure, technical expertise, and regulatory experience from more developed eastern cities to underdeveloped regions in central and western China. For instance, Jinan's collaborative data-sharing initiatives with surrounding prefectures offer a practical example of inter-city coordination in mitigating digital disparities.

6.3. Research Outlook

Future research should further investigate the interactions and synergies between DEM and other green development policies. A comparative analysis of the combined effects of DEM and complementary initiatives—such as carbon trading markets and green finance—would yield valuable insights into how integrated policy frameworks can enhance urban GTFEE. However, the current empirical evidence is constrained by data availability, particularly in regions with underdeveloped policy infrastructures, which may limit the generalizability of the findings. To address these limitations, future studies should conduct cross-policy comparative analyses to explore how different policies interact and reinforce each other across varying urban and socio-economic contexts, especially in cities or regions at different stages of green and digital development.

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