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Can the Marketization of Data Factors Improve the Efficiency of Urban Green Innovation? An Empirical Analysis of Both Intra-Domestic Firms and Spatial Perspectives

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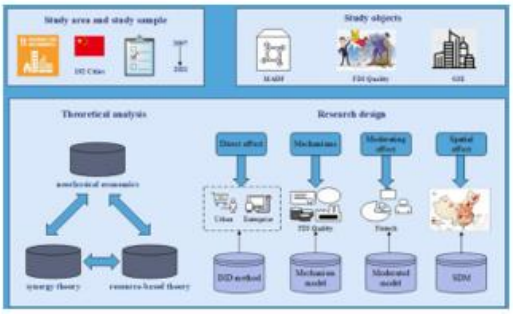
Graphical abstract



Abstract

Facilitating access to data resources and leveraging data factors to promote green innovation are essential for advancing digital strategies toward carbon neutrality. Since 2015, China has established data exchanges across multiple cities. Could this initiative enhance the efficiency of green innovation (GIE)? This study develops a research framework grounded in neoclassical economics and synergy theory, and investigates the relationship between the marketization of data factors (MADF) and GIE using panel data from 192 Chinese cities spanning the period from 2007 to 2021. Empirical evidence at both the city and firm levels demonstrates that the MADF significantly enhances GIE. The impact of MADF on GIE is more significant in non-Yangtze River Economic Belt (YREB) cities as well as in cities with higher intensity of environmental regulation. MADF can enhance GIE by attracting high quality foreign direct investment (FDI). Meanwhile, financial technology (Fintech) positively moderates the relationship between MADF and GIE. Furthermore, a notable spatial spillover effect exists between the MADF and the efficiency of green innovation. These findings offer practical guidance for advancing the comprehensive green transformation of economic and social development.

Keywords: green innovation efficiency; market-based allocation of data factors; spatial spillover effect; foreign direct investment; financial technology

1. Introduction

Amidst the current global climate change backdrop and escalating environmental worries, green innovation stands as a pivotal force for sustainable development (Hasan and Du 2023). To benefit from the green technological revolution, developing countries must implement proactive industrial, innovation, and energy policies and actions focused on green innovation (Sun *et al.* 2019). Pursuing a sustainable green innovation pathway has become essential for achieving the SDGs.

China considers innovation the primary driver of high-quality economic development and emphasizes the urgent need to mitigate excessive energy loss—prompted by rapid growth—through the deployment of green innovation technologies (Zhao *et al.* 2022). From 2016 to 2021, a cumulative of 471,000 green and low-carbon patents were granted worldwide, with 160,000, or 34%, being authorized by the China State Intellectual Property Office. This demonstrates China's significant role in advancing global green low-carbon technological innovation alongside maintaining stable economic growth. Therefore, exploring the drivers of green innovation in China can provide important insights for other developing countries to achieve coordinated economic and environmental development.

"Efficiency" is a critically important proposition (Fan *et al.* 2021). GIE is the ratio of outputs to inputs of technological innovation activities under resource and environmental constraints, and is intended to reflect the level of utilization of urban innovation resources (Liu *et al.* 2020). Despite the rapid increase in the total number of patents granted in China in recent years, issues such as scarcity of core green patents, low innovation efficiency, and significant technological gaps remain prevalent. This has led to Chinese innovation being stuck in the dilemma of "low-quality and low-efficiency" (Zhang *et al.* 2022). How to realize the "quality and efficiency" of green innovation has become an urgent issue for the government, society and enterprises in green transformation and development, and is also a solid guarantee to give full play to its huge positive externalities and provide powerful kinetic energy for the

Chinese government to effectively promote the supply-side structural reform and build a new development pattern.

Unlike traditional production factors, data factors are non-rivalrous and can be endlessly replicated and reused. They have a distinct life cycle as a result of economic activities and exhibit increasing returns to scale, scale effects, quality dependence, and a high degree of heterogeneity in value generation (Xiao *et al.* 2024). The global data factor market is currently experiencing rapid development. The United States has facilitated this by opening “non-sensitive” government data and diversifying data trading models. The European Union emphasizes data privacy protection and promotes the development of non-personal data aligned with industry differentiation. Japan advocates a “government-guided, private-led” development model to facilitate cross-border data flows. In recent years, China has always been promoting the marketization of data factors (see **Figure 1**). The “China Data Factor Market Development Report (2021-2022)” from China's National Industrial Information Security Development Research Center reveals that data factors have helped Chinese industrial firms reduce product development cycles by 15.33% on average and raise energy utilization rates by 10.19% on average. This indicates that data factors play a crucial role in driving GIE. Facilitating market-oriented distribution of data factors is essential for unlocking data dividends and enhancing GIE.

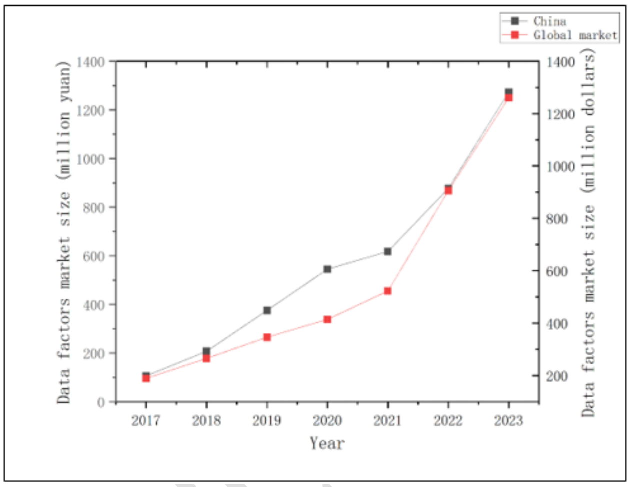


Figure 1. Data Factor Market Size. Data source: China National Industrial Information Security Development Research Center

Cities are the agglomerations of China's economic and social activities, and the engines for promoting scientific and technological innovation and economic growth (Zhang *et al.* 2022). Drawing on data from 192 prefecture-level cities in China between 2007 and 2021, this study examines how MADF improves the effectiveness of green innovation. The key marginal contributions are as follows:

Firstly, this study integrates data—the core element of the digital economy—and GIE—the key driver of the green economy—into a unified theoretical framework grounded in neoclassical economics and synergy theory. This framework establishes the theoretical basis for our study, enabling us to explore the connection between market-based distribution of data resources and GIE within the unique context of Chinese traits, while also broadening the current body of literature, thereby enriching the economic evaluation of MADF.

Secondly, we precisely measure GIE at the city level from an input-output perspective, and innovatively introduces FDI as a mediating variable and Fintech as a moderating variable to investigate the transmission path of the impact of MADF on GIE, providing clear directions for expanding the investigation into the antecedents of GIE and advancing the MADF.

Third, our study constructs a spatial econometric model to identify the spatial spillover effects of data factors and provides a reasonable explanation. This not only complements the analysis by broadening the perspective on data factors but also offers valuable insights into understanding the spatial diffusion mechanism of interregional data factors flows.

2. Literature review

2.1. GIE

GIE can be accurately gauged by the number of green invention patents or green utility model patents. However, this approach, while simple and effective, fails to capture the synergy between "green development" and "innovation-driven" concepts (Awan *et al.* 2021). It tends to overly emphasize the "outcome" and overlooks the innovation "process." This does not fully reflect GIE as the intersection of "green development" and "innovation-driven" concepts (Awan *et al.* 2021). The second method involves evaluating GIE by consolidating multiple indicators into a single indicator system using principal component analysis or entropy weight method (Hu *et al.* 2023). While these approaches are more comprehensive in terms of indicator selection, they do not fully consider the dynamic effect of GIE. Additionally, the former lacks interpretability, and the latter overlooks the importance of the indicators themselves (Sharif *et al.* 2018). Finally, the efficiency of green innovation is assessed using the Data Envelopment Analysis (DEA) method. Unlike the previous methods, DEA considers the entire input and output processes of green technological innovation, providing a more thorough and dynamic measure of its efficiency. However, the DEA analysis method is highly sensitive to data outliers and does not consider non-desired outputs in the innovation process. This often results in a high measured efficiency value. Therefore, many scholars utilize derived DEA models like the super-efficient SBM model, DEA-RAM, etc., to assess GIE (Liu *et al.* 2020).

At the macro level, government environmental regulation has long been recognized as a key driver in encouraging and guiding enterprises to enhance their green innovation capabilities. As a result, it has become one of the most extensively studied and intensively debated frontier topics in academic research. Existing literature has primarily focused on the effects of command-and-control regulations—such as the revised Environmental Protection Law (Yang and Wang 2021) and the New Energy Demonstration City policies (Lei 2024)—as well as market-based regulatory instruments, including low-carbon city pilot programs (Du *et al.* 2023) and carbon emissions trading schemes (Xiaobao *et al.* 2024), on GIE. However, the findings of these studies remain inconclusive. In addition to regulatory factors, climate change—including extreme weather events—as well as digital inclusive finance and green finance development, fiscal subsidies, and openness to foreign investment, may also exert significant influence on GIE (Lei and Xu 2025a; 2025b; 2024; Ahmad and Jabeen 2023; Cai *et al.* 2025a, 2025b).

Within the meso dimension, enhancements such as upgrading urban industrial structures (Lei *et al.* 2025), boosting green total factor productivity, enhancing the urban ecological environment, fostering clean energy development, and improving social governance effectiveness all play crucial roles in advancing GIE (Shang and Feng 2024). Furthermore, at the urban level, improvements in GIE contribute to the enhancement of urban employment conditions (Cai *et al.* 2024). At the industry level, Luo *et al.* (2019) highlights that strategic emerging industries, characterized by knowledge intensity and the integration of emerging technologies and sectors, play a significant role in driving GIE through dominance, emergence, and positive externalities. Furthermore, the clustering of high-tech and advanced manufacturing industries can reduce marginal external costs of production and consumption and enhance the quality and efficiency of green innovation (Huang *et al.* 2022).

At the micro level, factors such as market openness, media attention, ESG performance, executives' environmental awareness, digital investment, and venture capital play key roles in shaping the efficiency of corporate green innovation (Jin *et al.* 2023; Jin and Lei 2023; Lei and Xu 2025c). Media attention plays the role of an "information broker". By showcasing enterprises' positive green technological innovations, public recognition and support can be heightened. Conversely, media attention on negative practices like pollution discharge can apply social pressure on firms to enhance production and pollution control standards. This dual influence prompts enterprises to persist in green technological investment, ultimately leading to improved GIE (Hao *et al.* 2024). Drawing on social network theory, Lei and Xu (2025) utilized panel data from Chinese ChiNext-listed firms and found that venture capital institutions with higher network centrality significantly enhance corporate GIE.

2.2. MADF

MADF involves the fundamental trading of data factors through allocating them to pertinent production sectors, pricing them according to supply and demand dynamics, and adhering to the principle of equivalent exchange (Hoang *et al.* 2023). Most of the established studies focus on exploring the value structure, implementation path and social impact of MADF.

Data factors are essential data resources needed by the social economy for different aspects of production, distribution, circulation, consumption, and management of social services. They are business-attached and generate value only when combined with a specific business, not during the production stage (Lim *et al.* 2018). This process has undergone three stages: first, aggregating fragmented raw data into resources; second, delivering data products or services among various data subjects; and finally, integrating the data with specific scenarios to establish the "resourcefulness-productivization-assetivization" value creation chain of data factors. Based on the value chain theory, data factors achieve value realization through core activities along with supporting activities (see **Figure 2**) (Pan *et al.* 2022).

The process of MADF involves two key aspects. First, strengthening the capacity of data factor subjects is the basis for improving the efficiency of data elementization. Only by clarifying government and business roles, leveraging their expertise, and combining data with production factors like capital, technology, and talent can we maximize the value of data in economic, political, and social realms (Liang and Li 2023). Simultaneously, implementing a data classification and grading system enhances the efficiency of data factorization. This system delineates the value attributes of data, including scale, quality, applicability, scarcity, and potential utility. By doing so, it optimizes data search and matching processes, thereby reducing information costs associated with data fusion and innovation endeavors (Zong *et al.* 2017).

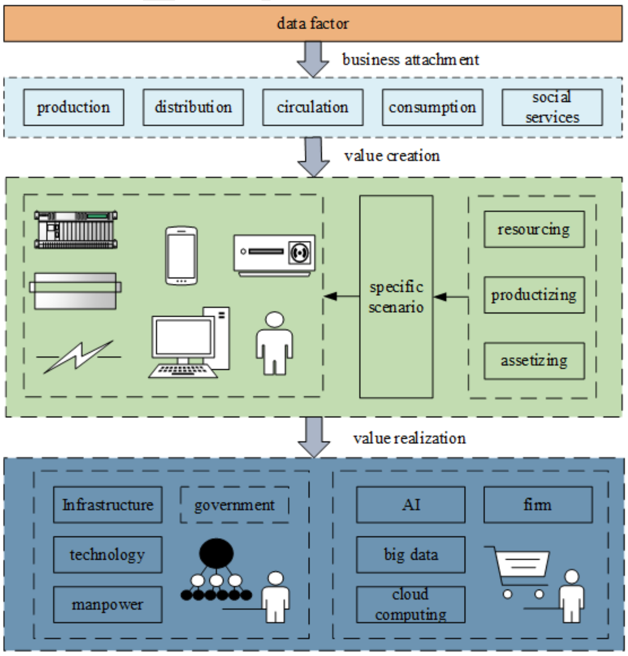


Figure 2. Data factor value creation and realization path

Secondly, developing a unified, interconnected, and robust data factor market system is a crucial step in expediting the enhancement of market-driven allocation of data factors (Zhang *et al.* 2022). In Europe, the United States, Japan, and other developed regions, information asymmetry has been successfully addressed through the implementation of a "data trust" model - a legal framework that offers independent data management. Alternatively, a "data intermediary" model, involving a third-party organization mediating between data providers and users, has also played a significant role in coordinating data relationships, thereby ensuring a robust data circulation mechanism (Paprica *et al.* 2020). In contrast, China's development of the data factor market has placed greater emphasis on government involvement. This has involved the formulation of a comprehensive national data factor market plan tailored to China's specific conditions, covering strategic, structural, and spatial dimensions (see **Table 1**). Additionally, data factor market-oriented circulation platforms have been established in various key locations such as Guizhou, Suzhou, Chengdu, Shanghai, Beijing, and others. By implementing standardized data classification and grading criteria, along with the introduction of appropriate labeling and descriptions for various data types and grades, China has delved into feasible data rights and authorization frameworks, transaction service modalities, reliable circulation models, product and service pricing strategies, and revenue-sharing mechanisms.

Table 1. Implementation of policies related to data factor trading in China

Year	Policy
2020	Opinions of the Central Committee of the Communist Party of China and the State Council on Building a More Complete Market-oriented Allocation System for Production Factors
2020	Opinions on Accelerating the Improvement of the Socialist Market Economic System in the New Era
2021	Action Plan for Building a High-standard Market System
2021	14th Five-Year Plan for Digital Economy Development
2022	Overall Plan for Comprehensive Reform Pilot of Market-oriented Allocation of Production Factors
2022	Opinions of the Central Committee of the Communist Party of China and the State Council on Accelerating the Construction of a Unified National Market
2022	Guiding Opinions of the State Council on Strengthening the Construction of Digital Government
2022	Opinions on Building a Data Foundation System to Better Leverage the Role of Data Elements
2023	Overall Layout Plan for Building Digital China
2023	Plan for the Reform of Party and State Institutions
2023	Provisional Regulations on the Accounting Treatment of Enterprise Data Resources
2023	Guiding Opinions on Data Asset Evaluation
2023	Guiding Opinions on Strengthening Data Asset Management
2024	Three-Year Action Plan for "Data Elements X" (2024-2026)

Source: Publicly available information

The social impact of the MADF involves industrial transformation, high-quality economic development and business transformation. Data factors can serve as substitutes for traditional factors of production, facilitating the restructuring of industries facing challenges related to information exchange, data collection, or high transaction costs (Gao and Li 2023). In line with the theory of optimal resource allocation, data factors can streamline production processes, reducing time and enhancing labor productivity. Additionally, they can expedite capital circulation by reducing production costs, thereby generating and realizing more value, ultimately fostering high-quality economic development. Lastly, as per resource-based theory, MADF can enhance workers' digital skills and expedite the evolution of diverse digital terminals and platforms into crucial production tools. This transformation leads to smarter manufacturing processes, optimized cost management, resource allocation, production, and sales operations within enterprises, ultimately facilitating the digital and intellectual transformation of businesses (Cheng *et al.*,2023).

2.3. Research gaps

While the importance of green innovation and MADF has been extensively researched and acknowledged, the majority of existing studies have primarily concentrated on macro, industry, or enterprise levels. However, it is evident that there is a notable gap in the literature at the city level, specifically in exploring the correlation between MADF and GIE. In 2014, China initiated the establishment of a data trading platform to define data ownership, accurately assess data value, facilitate equitable and mutually beneficial transactions, and create a secure and reliable environment for data circulation. Hence, leveraging the launch of China's data factor trading platform, we aim to investigate the impact of MADF on the efficiency of green innovation using panel data from 192 Chinese cities spanning from 2007 to 2021. Our goal is to enhance theoretical research in this area and offer insights that can guide other developing nations in harnessing digital opportunities and forging new economic paths at a practical level.

2.4. Research framework

This study draws on neoclassical economic theory and synergy theory to examine the value transmission path through which MADF influences GIE. The findings of Chen *et al.* (2024) indicate that urban GIE depends on the dynamic interactions and synergies among various social sustainability factors, including technological innovation, government regulation, population size, foreign investment, economic development, and industrial structure. No single factor alone is sufficient to drive improvements in GIE. This underscores the need for coordinated innovation efforts among governments, markets, enterprises, the public, and other stakeholders to foster integrated regional innovation (Jin *et al.* 2024; Li *et al.* 2023). According to neoclassical economic theory, data function as a key production factor that influences the decision-making behavior of market participants. The marketization of data factors enhances the value realization of data resources, improves the overall efficiency of resource allocation, and promotes both the transformation of government functions and the effectiveness of governance (Koch 2024; Rusak *et al.* 2021). By introducing market mechanisms, enterprises, and other specialized actors, the government facilitates the governance and processing of public data to generate data-driven products and services. Under the premise of ensuring data security, this approach supports regional enterprises by promoting data integration throughout the product life cycle. It enables a data-driven paradigm for the research and development of new technologies and products, offering solutions to challenges such as high R&D costs, long development cycles, and low commercialization rates (Jin *et al.* 2024).

Although the inclusion of FDI quality in analyzing the relationship between MADF and urban GIE may appear somewhat abrupt, it is well supported by both empirical evidence and real-world data. On the one hand, data possess characteristics of shareability and high value-added potential. The marketization of data factors expands information openness, reduces information asymmetry, and creates a favorable environment for foreign investment, thereby significantly facilitating the inflow of high-quality FDI (Clougherty and Zhang 2023). On the other hand, from the perspective of FDI classification, domestic firms competing with vertically integrated FDI in international markets may be incentivized to improve their GIE through "green technology spillovers." In contrast, horizontally integrated FDI primarily produces goods for domestic consumption and often sources intermediate inputs locally to meet consumer preferences—a process that may involve providing technical guidance to domestic suppliers (Chetia *et al.* 2025). In this context, the inflow of high-quality FDI can stimulate host-country firms to learn and imitate through the "technology demonstration effect" and the "market competition effect," thereby effectively enhancing regional GIE (Bai *et al.* 2023).

The research framework is shown in **Figure 3**

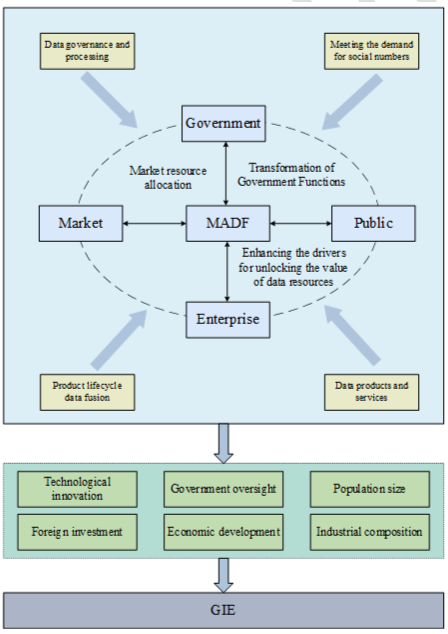


Figure 3. Research Framework

3. Methodology

3.1. Regression model

We establish a multi-period difference in differences (DID) model to empirically test the relationship between MADF and GIE. The DID method entails treating the implementation of a policy as a natural experiment. It involves assessing the net impact of policy implementation on the subject of analysis by incorporating a control group unaffected by the policy into the sample. This control group is then compared with the sample points initially impacted by the policy, creating an experimental group. Such an approach offers a more robust and dependable method for evaluating the policy effects. The data factor market evolves incrementally with the introduction of a data trading platform, aligning closely with the characteristics of a natural experiment. As a result, we develop Eq. (1) to empirically assess the influence of market-driven allocation of data factors on the efficiency of green innovation:

$$\mathrm{eff}_{i,t} = \beta_0 + \beta_1 \mathrm{market}_{i,t} + \sum \beta_2 X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (1)$$

Where *i* and *t* denote city and time, respectively. *eff* is the dependent variable in this study, denoting GIE. *market* is the independent variable, denoting the marketized allocation of data factors. *x* denotes a series of control variables, including employment status, science and technology, industrial structure, financing constraints, financial revenue and industrial base. μ and λ denote individual fixed effects and time fixed effects, respectively, and ε denotes a random error term.

In order to identify the impact of MADF on GIE, we adopt the research methodology of (Zhao *et al.* 2024) for empirical testing. This approach can effectively avoid the endogeneity problem faced in traditional mechanism testing models and make the test results more convincing in terms of causality. We set Eq. (2) as follows:

$$M_{i,t} = \beta_0 + \beta_3 \mathrm{market}_{i,t} + \beta_4 X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (2)$$

where $M_{i,t}$ are the mechanism variables in this study and the rest of the variables have the same meaning as Eq. (1). Eq. (1) and Eq. (2) constitute the mechanism-testing model. β_1 and β_3 represent the coefficients of the main explanatory variables in Eq. (1) and Eq. (2) correspondingly. If both β_1 and β_3 are statistically significant, the validated mechanism pathway is established.

Science, technology, and financial innovation can enhance asset allocation efficiency and expand financing avenues, thus easing funding constraints arising from information asymmetry and agency issues and fostering high-quality economic growth. We seek to ascertain if FinTech is able to moderate the connection between MADF and GIE. We set the Eq. (3):

$$\mathrm{eff}_{i,t} = \beta_0 + \beta_5 \mathrm{market}_{i,t} + \beta_6 X_{i,t} + \beta_7 Z_{i,t} \times \mathrm{market}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (3)$$

Where $Z_{i,t}$ is the moderating variable in this study and β_7 denotes the coefficient of the moderating variable with the core explanatory variable. The rest of the variables have the same meaning as Eq. (1). If β_7 is significant, it indicates that the moderating effect holds.

Data factors can enhance the digital integration of production factors and mobility between regions, fostering regional innovation networks through demonstrations, imitation effects, exchanges, and collaborations, thus bolstering innovation interconnections among regions (Lyu *et al.* 2023). Therefore, we construct a spatial econometric model to examine whether there is a spatial spillover effect of MADF on GIE. We establish Eq. (4) – Eq. (6):

$$\mathrm{eff}_{i,t} = \beta_0 + \beta_1 \mathrm{market}_{i,t} + \sum \beta_2 X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{4}$$

$$\mathrm{eff}_{i,t} = \beta_0 + \gamma \mathrm{Weff}_{i,t} + \beta_2 \mathrm{Wmarket}_{i,t} + \beta_3 X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{5}$$

$$\begin{aligned} eff_{i,t} &= \beta_0 + \gamma \mathrm{Weff}_{i,t} + \beta_1 \mathrm{market}_{i,t} + \rho \mathrm{Wmarket}_{i,t} \\ &+ \beta_2 X_{i,t} + \beta_3 WX_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \end{aligned} \tag{6}$$

where Eq. (4) is denoted as the Spatial Error Model (SEM), which is able to identify the effect of spatial variables on the measurement space. ϑ denotes the spatial error coefficient and W denotes the spatial weight matrix. Eq. (5) is expressed as a spatial lag model (SAR) that is able to identify the impact of the dependent variable in the region on the dependent variable in its neighboring regions. γ denotes the coefficient of the spatial lag term of *eff*. Eq. (6) denotes the Spatial Durbin Model (SDM), which is able to identify both the impact of explanatory variables on the explained variables within the region and reflect the spatial spillover impact of the explanatory variables in the region on the explanatory variables in neighboring regions. ρ denotes the coefficient of the spatial lag term of *market*.

The premise of constructing a spatial econometric model to test whether the MADF has spatial spillover effects on GIE is the need to verify whether GIE is spatially relevant. We analyze the spatial correlation of GIE using the Moran sI ' index. The Moran's I index is calculated as Eq. (7)-(9):'

$$\text{Moran's I} = \frac{\sum_{a=1}^{n}\sum_{b=1}^{n} W_{ab}(\, eff_a - \overline{eff})\left(eff_b - \overline{eff}\right)}{S^2 \sum_{a=1}^{n}\sum_{b=1}^{n} W_{ab}} \tag{7}$$

$$S^2 = \frac{1}{n}\left(eff_a - \overline{eff}\right) \tag{8}$$

$$\overline{eff} = \frac{1}{n} eff_a \tag{9}$$

where S^2 is the variance of *eff*, $\overline{eff}$ is the mean value of *eff*; *n* is the number of sample cities. If *Moran's I* is greater than 0 it means that there is a positive spatial correlation between the provinces, and vice versa for negative correlation.

The matrix we construct is the economic distance matrix W_1 and Geographical distance matrix W_2 constructed as in Eq. (10) and Eq. (11):

$$W_1 = \frac{1}{\left|\overline{y}_i - \overline{y}_j\right|} \tag{10}$$

$$W_2 = \frac{1}{{d_{ij}}^2} \tag{11}$$

where d_{ij} is the distance between city *i* and city *j*; and $\overline{\mathrm{y}}_{\mathrm{i}}$ is the mean value of GDP per capita in city *i* over the sample period.

3.2. Variable description

3.2.1. GIE (eff)

As previously mentioned, the super-efficient SBM model, in comparison to other measurement methods, effectively addresses the input-output variable slackness issue associated with the DEA method. It places emphasis on analyzing the impact of non-desired outputs on efficiency, enabling a more detailed decomposition of efficiency values for comparison and resulting in more precise measurement outcomes. Therefore, we incorporate capital and labor constraints as input indicators, green patent grants as desired output indicators, and utilize the entropy weighting method to measure the urban environmental pollution index as a non-desired output. The super-efficient SBM model is employed to assess GIE. Specific measurement formulas and measurement indicators are shown in **Table 2** and Eq. (12)-(13).

$$\min\rho = \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\overline{x}_i}{x_{ik}}}{\frac{1}{s_1+s_2}\left(\sum_{o=1}^{S_1}\frac{\overline{y}_o}{y_{ok}} + \sum_{u=1}^{S_2}\frac{\overline{z}_u}{z_{uk}}\right)} \tag{12}$$

$$s.t.\begin{cases} \overline{x}_i = \overline{x}_{i0} + s^-, i = 1,2,\ldots m \\ \overline{y}_o = \overline{y}_{ok} - s, o = 1,2,\ldots s_1 \\ \overline{z}_u = \overline{z}_{uk} + s, o = 1,2,\ldots s_2 \\ \overline{x} \geq x_0, 0 \leq \overline{y}_o \leq y_k, \overline{z}_u \geq z_k, \overline{z}_u \geq 0 \\ \overline{x} \geq \sum\limits_{j=1, j\neq 0}^{n} x_j * \lambda_j \\ \overline{y}_o \leq \sum\limits_{j=1, j\neq 0}^{n} y_{oj} * \lambda_j \\ \overline{z}_u \geq \sum\limits_{j=1, j\neq 0}^{n} Z_{oj} * \lambda_j \\ 0 \leq \lambda_j \end{cases} \tag{13}$$

Eq. (12) is the objective function and Eq. (13) is the qualification. Where *n* is the number of decision making units (DMUs) and *m* is the number of input variables. s_1 and s_2 represent desired and undesired outputs, respectively. *x*, *y* and *z* are the elements in the input, desired and undesired output matrices, respectively, and λ is the weight vector.

Table 2. The index system of GIE

Category	First-level Indicators	Notes	Unit
Input variables	Capital investment	Expenditure on science and technology	RMB 10,000
	Labor input	Number of employees in scientific and technological activities	10,000 people
Output variables	Technological output	Number of Green Patents granted	items
	Non-desirable output	Wastewater discharge	10,000 tons
		SO_2 Emissions	10,000 tons
		Smoke and dust Emissions	10,000 tons

3.2.2. MADF (market)

We utilize the establishment of a data factor platform as a proxy variable for MADF (refer to the **Figure 4** for the implementation in the sample city). If the sample city establishes a data trading platform in the current year, the *market* variable is set to 1 in the current year; otherwise, it remains at 0. In cases where the sample city does not establish a data trading platform, the *market* variable consistently stays at 0.

3.2.3. Control variables

To enhance the accuracy of our analysis, we referenced the research findings of Bai *et al.* (2023) and Wang *et al.* (2024) when selecting control variables. These variables include human capital, science and technology expenditures, industrial structure, financing constraints, fiscal revenues, and industrial base. The measurements for these variables are detailed in the **Table 2** provided.

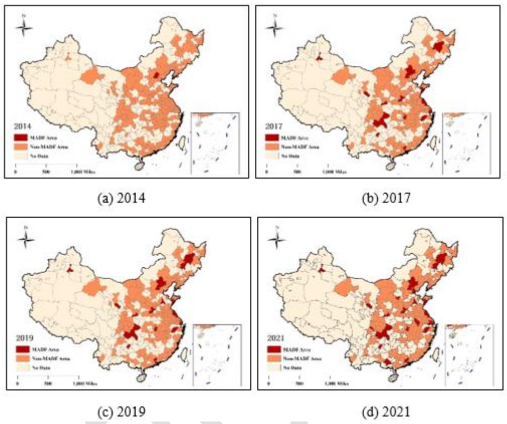


Figure 4. Area of MADF

3.2.4. Mediating and moderating variables

This article examines the impact of foreign investment in shaping the mechanism and the moderating role of fintech. Specific measurements are detailed in **Table 3.**

Table 3. Descriptive statistics

Variables (unit)	Definition	Mean	Max	Min
Human capital (10,000 people)	Number of employees in urban units at the end of the period	12.9323	16.1048	2.9172
Science and Technology Expenditure (RMB 10,000)	Science and Technology Expenditure	10.3784	15.5293	6.4345
Industrial Structure (%)	Proportion of the tertiary industry in the regional GDP	41.1202	83.8700	11.8000
Financing Constraints (RMB 10,000)	Year-end balance of loans from financial institutions	16.4621	20.5984	12.7682
Fiscal Revenue (RMB 10,000)	Local public budget revenue	13.9540	18.1696	9.9439
Industrial Base (RMB 10,000)	Current assets of industrial enterprises	15.9163	19.6585	10.2741
Total Foreign Investment (RMB 10,000)	Actual amount of foreign investment utilized in the current year	10.2593	14.9413	2.3036
Industrial Foreign Investment (RMB 10,000)	Total industrial output value of foreign-invested enterprises	12.0791	18.8335	0.0000
Fintech (%)	Proportion of fintech term frequency in annual reports	2.7642	7.4911	0.0000

With the exception of industry structure, we log all other control variables and all mediating and moderating variables to ensure that all data are in a similar dimension.

3.3. Data sources

We have selected a panel of 192 prefecture-level cities in China as our sample data, covering the period from 2007 to 2021. On one hand, international organizations such as the United Nations Environment Programme (UNEP) introduced the definition of the green economy for the first time in 2007 in the report "Green Jobs: Achieving Decent Work in a Low-Carbon, Sustainable World," describing it as "an economy that values people and nature and creates decent, well-paying jobs." This designation of 2007 as a pivotal year underscores the strategic adoption of green technologies in major countries globally. On the other hand, limited by the missingness of some of the variables, it is difficult to include data from 2022 and later years for empirical testing, so we set the sample cutoff to 2021. We use linear interpolation to impute missing data and excluded cities with significant data gaps, resulting in a final sample of 192 cities. Our data sources includes the China Urban Statistical Yearbook, the China Environmental Statistical Yearbook, and the CSMAR database.

4. Results and discussions

4.1. Baseline regression results

We use Eq. (1) to examine the correlation between MADF and GIE, and the regression results are displayed in **Table 4**. We cluster standard errors at the city level. Column (1) displays regression results without controlling for any additional variables. Column (2) includes control variables but does not consider time fixed effects. Column (3) includes control variables but does not consider city fixed effects. Column (4) incorporates control variables and controls for both time fixed effects and city fixed effects. The *market* coefficient shows a consistently significant positive impact at the 1% level, irrespective of control variables, time, and city fixed effects. From column (4), we can see that the coefficient of *market* is 0.0473, meaning that MADF can increase GIE by 4.7%. This indicates that MADF plays a crucial role in enhancing GIE. Based on the preceding theoretical analysis, the influence of MADF on GIE necessitates the collaborative efforts of multiple stakeholders. Having confirmed the overall impact of MADF on GIE, it is essential to further examine whether MADF also improves the GIE of enterprises within the domain. If this is the case, it would provide strong support for the validity of our earlier analysis. Utilizing data from A-share listed enterprises, we aggregate the samples at the city level and identified 1,135 listed firms (The sample includes 1,135 firms rather than all listed companies, as we excluded those with a significant number of missing values after applying linear interpolation to supplement the sample data.). The GIE of enterprises within each city domain is measured using the ratio of R&D inputs to R&D outputs (i.e., green patents), which serves as the explanatory variable in the regression analysis. The regression results are presented in Column 5 of **Table 4**. The results indicate that the coefficient of *market* is 0.6408 and remains statistically significant at the 5% level. This suggests that MADF also exerts a significant positive effect on GIE at the firm level. From the perspective of economic significance, this finding reinforces the notion that the improvement of urban GIE through MADF requires coordinated efforts among government, market, enterprises, and the public to achieve meaningful outcomes.

Our conclusions are consistent with the findings of (Liao *et al.* 2024). One possible reason is that the MADF enables a broader range of market participants to engage in competition independently and equitably. This approach mitigates issues of price distortion and discrimination resulting from external interventions, addresses information asymmetry prevalent in traditional factor markets, and achieves precise alignment of green innovation elements (Yang and Wang 2021). On the other hand, the MADF has enhanced the integration of data production factors with traditional production factors, facilitating the movement of all resources towards cities with high production efficiency (Ge *et al.* 2022). This dynamic allows for the free and efficient flow of innovation factors, improving the alignment between urban innovation entities and these factors. As a result, cities can more readily access, learn from, and absorb advanced external knowledge and technology, which helps to reduce innovation costs and risks while promoting GIE (Li *et al.* 2024).

Table 4. Baseline regression results

	(1)	(2)	(3)	(4)	(5)
	eff	**eff**	**eff**	**eff**	**eff**
market	0.0422***	0.0476***	0.0492***	0.0473***	0.6408**
	(7.98)	(9.05)	(9.50)	(8.97)	(2.59)
human capital		0.0035	0.0061**	0.0029	-0.5963
		(1.18)	(2.14)	(0.96)	(-1.40)
science and technology expenditure		-0.0163***	-0.0157***	-0.0163***	-0.0387
		(-7.78)	(-7.92)	(-7.70)	(-0.15)
industrial structure		0.0005**	0.0005**	-0.0001	0.0124
		(2.29)	(2.29)	(-0.24)	(0.46)
financing constraints		0.0075**	0.0053	0.0029	0.9257*
		(1.99)	(1.42)	(0.67)	(1.72)
fiscal revenue		0.0081*	0.0066	0.0002	1.1112
		(1.83)	(1.44)	(0.03)	(1.60)
industrial base		0.0070*	0.0057*	0.0059	-0.4247
		(1.83)	(1.68)	(1.45)	(-0.83)
_cons	0.0070**	-0.2281***	-0.1971***	-0.0131	-17.3425
	(2.20)	(-5.68)	(-5.41)	(-0.15)	(-1.53)
City Fe	Yes	Yes	No	Yes	Yes
Year Fe	Yes	No	Yes	Yes	Yes
Firm Fe	No	No	No	No	Yes
N	2880	2880	2880	2880	17025
R^2	0.0639	0.0739	0.0849	0.0881	0.238

*Note: t statistics in parentheses, *p < 0.1, ** p < 0.05, *** p < 0.01*

4.2. Robustness test

4.2.1. Parallel trend test

Prior to employing the DID model, it is essential to conduct a parallel trend test to verify that the GIE of both the control and experimental groups exhibit consistent trends prior to the MADF. For this purpose, we borrowed the test from (Pan and Tang 2021) and used the event study method to conduct a parallel trend test. We set the base year as 2014 and selected the three years preceding it and the five years following it as the sample period for the parallel trends test. The test results are shown in **Figure 5**. It can be found that the coefficients of *market* are all positive but not significant before the implementation of the MADF. And in the second year after the implementation of the MADF, the confidence interval of *market* are not included in 0, and significantly positive. This indicates that we pass the parallel trend test.

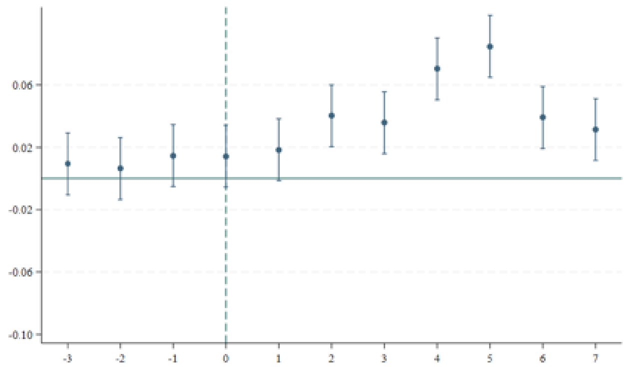


Figure 5. Parallel trend test.

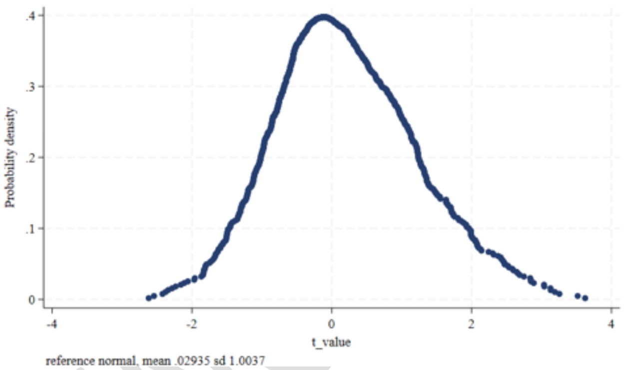


Figure 6. Placebo test

4.2.2. Placebo test

To mitigate the influence of potential unobservable factors on the GIE, we conduct a placebo test by randomly sampling the treatment group variables multiple times and re-running regressions 1000 times. We examine whether the kernel density plots of the *market* coefficients or observations post-randomization are centered around 0 and if they significantly deviates from their actual values. The results of the placebo test, depicted in **Figure 6**, demonstrate that the t-values of *market* are normally distributed around 0, affirming the success of the placebo test

4.2.3. Other robustness tests

Firstly, we shrink the sample at the 1% level in order to avoid the effect of sample outliers on the test results and regress them again. The results are shown in Column (1) of **Table 5**, where we can find that the coefficient of *market* remains significantly positive at the 1% level, which indicates that our regression results remain robust after accounting for the effect of outliers.

Second, we account for the potential influence of other concurrent policies during the sample period. In addition to the MADF, several other policy initiatives—such as the Smart City Pilot Policy (Yan *et al.* 2023), the Carbon Emissions Trading Policy (Zhao *et al.* 2024), the Ecological Compensation Incentive Policy (Chang *et al.* 2024), the Digital Government Initiative (Big Data Management Institutional Reform) (Zhang *et al.* 2025), and the Green Financial Reform Pilot Zone Policy (Zhang 2023)—may have also affected urban GIE. To assess whether these policies interfered with our estimation results, we introduce dummy variables representing each policy into the regression model and re-estimated the specifications. The results are reported in columns (2) through (6) of **Table 5**. It can be observed that the coefficient on the *market* remains significantly positive at the 1% level, with an estimated value fluctuating around 0.04, which is broadly consistent with the baseline regression results. This finding suggests that our estimation results are robust.

Furthermore, as the level of digital economic development continues to rise, the value of data factors has accelerated in recent years. Due to limitations in data availability, we extend the sample period to 2023 to further examine the impact of MADF on GIE. Cities with severe data gaps were excluded, resulting in a final sample of 130 cities for the re-estimated regression analysis. The results are reported in Column (1) of **Table 6**. It can be observed that the coefficient of *market* remains significantly positive at the 1% level, with an estimated value of 0.0327, thereby confirming the robustness of our findings.

In addition, the construction of a DID model requires the use of binary explanatory variables, which may overlook the gradual and continuous nature of the data trading market development process. To this end, we employ a text analysis approach based on publicly available annual reports of listed companies to extract the word frequency of terms related to data assets (plus one), and then took the logarithm. These values are aggregated by the registration location of firms at the prefecture-level city, and we computed the average logarithmic word frequency of data asset terms for each city. This measure was then interacted with the construction of the data factor market to create a proxy variable for MADF, which was subsequently used in a re-estimation of the regression model. The regression results are presented in Column (2) of **Table 6**. It can be observed that the coefficient on the interaction term *factors * market* remains significantly positive at the 1% level, with an estimated value of 0.971, indicating that our findings are robust.

Table 5. Other robustness tests (a)

	(1)	(2)	(3)	(4)	(5)	(6)
	eff	eff	eff	eff	eff	eff
market	0.0501***	0.0476***	0.0456***	0.0137***	0.0467***	0.0358***
	(9.71)	(9.05)	(8.62)	(2.86)	(8.01)	(6.20)
smart city		-0.0009				
		(-0.28)				
ets			0.0165***			
			(3.53)			
ecological compensation				-0.0004		
				(-0.15)		
digital policy					-0.0026	
					(-0.53)	
green finance reform						-0.0040
						(-0.12)
_cons	-0.1937***	-0.0140	-0.0125	-0.0688	-0.0967	-0.0857
	(-5.04)	(-0.16)	(-0.15)	(-0.97)	(-0.82)	(-0.73)
City Fe	Yes	Yes	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0902	0.0881	0.092	0.073	0.089	0.072
N	2880	2880	2880	2880	2880	2880

*Note: t statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Table 6. Other robustness tests (b)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	eff	eff	market	eff	market	eff	eff
market	0.0327***			0.4274***		0.0763***	0.971**
	(6.32)			(4.02)		(11.14)	(1.98)
factors*market		0.0295***					
		(7.38)					
financial expenditure			0.0288***				
			(3.66)				
L.market					0.9443***		
					(86.44)		
F			95.45		1419.56		
_cons	0.0577	-0.0451	-0.9458 ***	0.0558	-0.1777***	-0.1670***	-16.71*
	(0.68)	(-0.46)	(-10.90)	(0.69)	(-4.91)	(-7.70)	(-2.21)
City Fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0902	0.0881	0.1887	0.0084	0.7870	0.1381	0.0920

*Note: t statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Table 7. Standard coal coefficients

Energy	Coefficients	Unit
Fuel oil	1.7143	tons of standard coal/ton
Natural gas	13.3	Tons of standard coal per 10,000 m^3
Electricity	1.229	Tons of standard coal per 10,000 kWh

Next, we conduct an endogeneity test using the instrumental variable method. Government fiscal expenditures are selected as the instrumental variable, and we utilize the two-stage least squares method to estimate Eq. (1). The results of the first stage regression are presented in column (3) of **Table 6**, indicating that the regression outcomes for government fiscal expenditures are notably positive. Furthermore, the F-value statistic surpasses 10, suggesting that the choice of instrumental variables is deemed appropriate. Moving on to the second-stage regression, showcased in column (4) of Table 6, the coefficient estimates of *market* remain significantly positive at the 1% level, reaffirming the robustness of the earlier regression results. In addition, following the approach of Song and Han (2022), we use the lagged value of the core explanatory variable, *L.market*, as an instrument for market to conduct an endogeneity test. It can be observed that the coefficient of *L.market* is significantly positive at the 1% level in the first stage, and similarly, the coefficient of *market* remains significantly positive at the 1% level in the second stage. This further confirms that the empirical results pass the endogeneity test.

Finally, to further verify the robustness of the regression results, we follow the methodology of Yue *et al.* (2025) and, based on equations (12) and (13), redefine the expected outputs as the city's per capita GDP, the number of green patent grants, and energy efficiency. The measurement approach of *Energy Efficiency* is illustrated in the corresponding equation (14), where *Energy* denotes the total energy consumption of each city. It is calculated by summing the consumption of three types of energy resources—fuel oil (tons), natural gas (10,000 cubic meters), and electricity (kilowatt-hours)—each multiplied by its respective standard coal conversion factor (see Table 7). *GDP* represents the actual GDP of each city over the years (unit: 100 million yuan). We measure GIE from a multidimensional perspective and re-estimated the model accordingly. The results are presented in the corresponding table. It can be observed that the coefficient on the *market* remains significantly positive at the 5% level, indicating that our regression results are robust.

$$\text{Energy Efficiency} = \frac{\text{Energy}}{\text{GDP}} \tag{14}$$

4.3. Heterogeneity

4.3.1. Regional heterogeneity

The YREB spans 11 provinces in China, covering 21.4% of the country's land area and hosting over 40% of China's total population and economy. It boasts significant resource, environmental, and technological advantages, serving as a crucial driver for China's innovation-oriented growth and a key focal point for the nation's environmentally-friendly green development strategy. Green innovation, serving as a new driving force to reconcile ecological preservation and economic expansion, has emerged as the cornerstone for fostering high-quality development within the YREB region. Therefore, we divide the sample into two subsamples of non-YREB cities and coastal cities for regression to examine whether there is regional heterogeneity in the impact of MADF on GIE. (see **Figure 7**).

The regression results are shown in column (1) and column (2) of Table 8. Where column (1) denotes the subsample of cities not along the YREB and column (2) denotes the subsample of cities along the belt. The result reveals that the coefficient of *market* is significantly positive at the 1% level in the subset of non-YREB cities, whereas it is negative but not statistically significant in the subset of cities within the belt. This indicates that the MADF notably boosts the GIE of non-YREB cities to a greater extent.

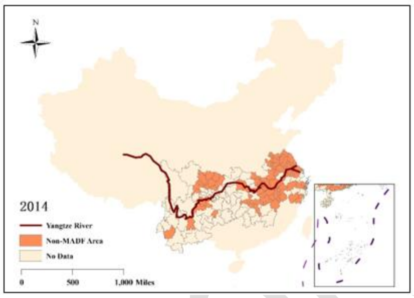


Figure 7. Sub-sample distribution of cities along the YREB

This result is somewhat different from the findings of Zeng *et al.* (2021). One possible reason for the challenges faced by cities along the Yangtze River Economic Belt is their long-standing rough development pattern, which has led to significant resource and environmental pressures. This situation hinders the endogenous momentum for innovation development in these cities (Huang and Wang 2020). In certain regions of the YREB, the intensity of development and construction has exceeded the ecological and resource carrying capacity, leading to persistently low energy efficiency levels (Cui *et al.* 2025). Moreover, carbon emissions are highly concentrated in the lower reaches of the YREB, particularly in Shanghai, Jiangsu, and Zhejiang (An *et al.* 2025; Chetia *et al.* 2025). Under the dual pressure of both "digitalization" and "greening," upstream regions struggle to swiftly adapt their responsiveness, resilience, and processing capabilities. This has further exacerbated regional disparities arising from differences in geographical location, resource endowment, and industrial foundations (Qiu *et al.* 2025). Additionally, while the digital economy in the Yangtze River Delta cities contributes to about 44% of GDP, the uneven growth of the digital economy in other cities along the Economic Belt creates invisible barriers to the smooth operation of data factors. Consequently, this imbalance impedes the establishment of a unified and efficient operation mechanism for the regional data factor market, thus limiting the potential of data factors to drive innovation (Luo *et al.* 2022).

Table 8. Heterogeneity tests

	(1)	(2)	(3)	(4)
	eff	eff	eff	eff
market	0.0793***	-0.0077	0.0140	0.0740***
	(10.13)	(-1.59)	(1.41)	(10.27)
_cons	0.0089	-0.0649	-0.0739	-0.0113
	(0.07)	(-0.78)	(-0.61)	(-0.08)
Control	Yes	Yes	Yes	Yes
City Fe	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes
N	1800	1080	1369	1511
R^2	0.1182	0.0873	0.0949	0.1278

*Note: t statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Table 9. Mechanism tests

	(1)	(2)	(3)	(4)	(5)
	FDI	**IFDI**	**FDI**	**eff**	**eff**
market	0.2079**	-0.2369**		0.0008*	0.0159***
	(2.29)	(-2.52)		(1.83)	(2.58)
L2.FDI			0.0992***		
			(2.76)		
F			1610.58		
Fintech*					
market					0.1003***
					(9.47)
_cons	-11.9206***	0.7811			-0.0329
	(-7.88)	(0.50)			(-0.39)
Control	Yes	Yes			Yes
City Fe	Yes	Yes			Yes
Year Fe	Yes	Yes			Yes
N	2781	2860	2880	2880	2880
r2_w	0.2320	0.9557	0.8249	0.1125	0.1178

Note: t statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.3.2. Heterogeneity of environmental regulatory intensity

Under the guidance of the new development concept, environmental quality indicators such as green innovation have been included in the performance appraisal of various local governments in China. Porter's hypothesis posits that environmental protection strongly fosters innovation when the compensating effect of environmental regulation outweighs the offsetting effect (Han *et al.* 2024). However, there is no consensus on whether this innovation compensation effect varies based on the intensity of environmental regulation. We regress the sample into two subsamples, weak environmental regulation intensity cities and strong environmental regulation cities, based on the word frequency of environmental protection in city government work reports to examine the heterogeneity of environmental regulation intensity. The regression results are shown in Table 8, column (3) and column (4). Where column (3) represents the weak environmental regulation intensity city subsample and column (4) represents the strong environmental regulation intensity subsample. The results show that the coefficient of *market* is not significant in the weak environmental regulation intensity city subsample. However, in the strong environmental regulation intensity subsample, the coefficient of *market* is significantly positive at the 1% level, with a coefficient value of 0.0740. This suggests that the MADF notably boosts the GIE of cities with stronger environmental regulations.

Our results align with the conclusions of (Jing and Liu 2024). This could be attributed to the fact that enhancing GIE, a pivotal factor in driving the green transformation of urban economies, necessitates robust environmental regulations and effective enforcement, highlighting the importance of environmental regulation intensity in this context. According to the theory of innovation compensation, when faced with external environmental regulatory pressures, sectors within cities tend to enhance the efficiency of green innovation to comply with environmental regulations, consequently mitigating the impact of these regulations on their operational costs.

4.4. Mechanism test

Based on our initial validation of the MADF and GIE, we aim to further explore the mechanisms between the two. It has been demonstrated that the MADF can facilitate the influx of FDI, leading to an increase in environmental tax revenue that assists the government in managing the country's environmental quality. However, excessive FDI inflows may have negative implications for the environment (Song and Han 2022).

Therefore, we examine the mechanism from the perspective of FDI quality with the aid of Eq. (2). The regression results are shown in column (1) and column (2) of Table 9. Where column (1) shows the test results of the FDI mechanism and column (2) shows the test results of the mechanism of industrial foreign capital inflow. It can be found that the coefficient value of *market* in column (1) is 0.2079 and is significantly positive at the 5% level. The coefficient value of *market* in column (2) is -0.2369 and is significantly negative at the 5% level. This suggests that MADF can enhance the efficiency of green innovation by promoting FDI inflows and reducing the total amount of industrial foreign investment, respectively.

The potential reasons include, on one hand, that the MADF accelerates inter-regional factor flows. This process enhances the collection, storage, and sharing of vast amounts of data, which improves the breadth and depth of information absorption within cities. As a result, it lowers the information search costs and time expenditures for foreign enterprises in the investment market, effectively attracting FDI. On the other hand, the traditional model of rough development has attracted a substantial influx of energy-intensive and high-polluting foreign industrial investments into the Chinese market. However, with the implementation of MADF, the flow of these data has increased the Poisson flow density of successful iterative innovations. This dynamic encourages foreign-funded enterprises to expand their short-term user base through iterative innovation, thereby enhancing their own innovation capacity by utilizing data generated by these users. Consequently, low-quality, high-emission foreign industrial firms face increasingly intense competition and are gradually retreating from the Chinese market. This process further improves the quality of regional FDI, enhances technology diffusion from foreign investors, facilitates technology absorption by local firms, and ultimately boosts GIE. (Song and Han 2022).

Although our mechanism testing approach can mitigate endogeneity concerns to some extent, FDI may still tend to flow into regions with inherently cleaner and more efficient green technology endowments. Therefore, we employ an instrumental variable approach to further test for potential endogeneity. In selecting the instrumental variables, we follow the approach proposed by Song and Han (2022), using FDI inflows lagged by two periods as instruments. We employ the least squares method to conduct the regression analysis. The results are reported in columns (3) and (4) of Table 9. As shown, in the first stage, the coefficient on *L2.FDI* is significantly positive at the 1% level. In the second stage, the coefficient on the market variable remains significantly positive at the 10% level, suggesting that our mechanism test results are not affected by endogeneity concerns. (The corresponding results based on total industrial FDI are available upon request.)

We conduct additional testing to determine if FinTech acts as a positive moderator in the association between the MADF and the efficiency of green innovation. This is due to the inherent synergy between data factors and FinTech. The MADF furnishes FinTech with enhanced capabilities in data collection, processing, storage, mining, and other technological functions. Simultaneously, the MADF provides more data collection, data processing, data storage, data mining and other technologies and ways for Fintech, while the application of Fintech can deeply explore data resources and narrow the digital divide, releasing the advantageous potential of massive data and rich scenarios, and then play the role of the engine of the market allocation of data factors on the efficiency of green innovation. (Chen *et al.* 2022).

We empirically test the moderating effect of Fintech with the help of Eq. (3) and the results of the test are presented in column (5) of Table 9. It can be found that the coefficient of the interaction term between *Fintech* and *market* is 0.1003 and is significantly positive at 1% level. This indicates that our analysis holds and that Fintech does play a positive moderating role in the relationship between MADF and GIE.

4.5. Spatial spillover effects

The previous analysis has validated the influence of MADF on GIE. However, there is a potential for estimation result bias arising from overlooking the spatial correlation among cities. This study further employs the SDM to incorporate both geographical and economic distance matrices, in order to examine the impact of the market-based allocation of data factors on the target region as well as on economically connected regions—that is, to identify the spillover effects arising from the implementation of such allocation mechanisms. First, we use Equations (7) through (9) to calculate the spatial effects for the period 2007–2021. The results are presented in Table 10. It can be observed that although the Moran's I index for urban GIE under the geographic distance weighting matrix was generally greater than zero throughout the sample period, the associated p-values were mostly above 0.1. In contrast, under the economic distance weighting matrix, the Moran's I index remained positive, and the corresponding p-values were generally below 0.1. These findings provide preliminary evidence that, compared to the geographic distance matrix, the economic distance matrix better satisfies the selection criteria and applicability conditions for implementing spatial econometric models. This may be attributed to the fact that the diffusion of GIE often relies more on industrial linkages, value chains, and economic connectivity than on mere geographical proximity. Economic distance matrices are better suited to capturing structural similarities across regions.

Table 10. Moran's I index of geographic distance weighting matrix

Year	Moran's I	Z	P
2007	0.029	3.551	0.000
2008	0.012	1.772	0.076
2009	0.010	1.575	0.115
2010	0.014	2.069	0.039
2011	0.001	0.942	0.346
2012	0.005	1.322	0.186
2013	0.001	0.868	0.385
2014	0.004	1.214	0.225
2015	0.003	1.286	0.199
2016	0.006	1.551	0.121
2017	0.009	1.860	0.063
2018	-0.006	-0.071	0.943
2019	-0.005	0.029	0.977
2020	0.001	1.173	0.241
2021	0.002	1.336	0.181

To assess whether the SDM can evolve into a spatial lag model or a spatial error model, the study presents the LR test statistic results for the spatial autocorrelation examination of GIE using the economic distance spatial weight matrix (refer to Table 12). The LR test statistic notably rejects the null hypothesis that there is no significant spatial autocorrelation at the 1% level, reaffirming the presence of positive spatial autocorrelation in GIE. Based on the outcomes of the Hausman test, the spatial Durbin model is selected to estimate the spillover effect of MADF.

Table 11. Moran's I index of economic distance matrices.

Year	**Moran's I**	**Z**	**P**
2007	0.051	2.170	0.030
2008	0.037	1.675	0.099
2009	0.050	2.107	0.035
2010	0.044	1.891	0.050
2011	0.041	1.768	0.077
2012	0.045	1.918	0.055
2013	0.040	1.725	0.085
2014	0.019	0.951	0.342
2015	0.047	2.001	0.045
2016	0.051	2.157	0.031
2017	0.005	0.410	0.682
2018	0.027	1.263	0.206
2019	0.052	2.212	0.027
2020	0.035	1.568	0.117
2021	0.069	2.872	0.004

Table 12. Spatial autocorrelation retest

test	**statistic**	**p**
LM-lag	5.458	0.019
R-LM-lag	23.954	0.000
LM-err	13.272	0.000
R-LM-err	31.768	0.000
LR-lag	32.77	0.004
LR-err	3274.16	0.000
Hausman	32.28	0.000

Table 13. Spatial spillover effects

variable	**(1)**	**(2)**	**(3)**	**(4)**
	eff	**eff**	**eff**	**eff**
market	0.0415***	0.0835***	0.0445***	0.0390***
	(8.04)	(8.76)	(8.52)	(4.16)
sigma2_e	0.0018***			
	(37.45)			
Control	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes
City Fe	Yes	Yes	Yes	Yes
N	2880	2880	2880	2880

*Note: t statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

The estimated outcomes regarding the spatial spillover effects of the influence of MADF on GIE are depicted in Table 13. Specifically, in column (1), the estimation results of creating the economic distance matrix within the SDM model framework are presented. Notably, the coefficient for *market* is calculated to be 0.0415, demonstrating a statistically significant positive impact at the 1% level. This suggests that MADF indeed exerts a noteworthy positive spillover effect. We further apply partial differentiation to the variables in the spatial Durbin model to decompose the spatial spillover effects of MADF on GIE into total, direct and indirect effects. The regression results are shown in columns (2)-(4) of Table 13. Among them, Column (2), Column (3) and Column (4) represent the regression results of total effect, direct effect and indirect effect, respectively.

It can be found that the coefficient of the direct effect is 0.0445 and the coefficient of the indirect effect is 0.0390, and both of them are significantly positive at the 1% level. This indicates that the implementation of MADF not only promotes the GIE of the city, but also promotes the GIE of cities with closer economic ties. This reinforces the notion that data factor trading and circulation facilitate cross-regional flow, cross-industry sharing, and cross-process application of data factors. Existing research suggests that data factorts can drive inter-regional resource sharing and collaborative development, rather than the unilateral flow of resources (Luo *et al.* 2025). This process not only optimizes the allocation of data resources at the regional and industrial levels, enabling more effective support across various sectors and links of the economy and society, but also significantly enhances the efficiency of economic and social operations in neighboring regions, thereby fostering high-quality development.

5. Conclusions and policy recommendations

In the fast-evolving landscape of the digital economy, leveraging the fundamental resources and multiplier effect of data to boost the efficiency of green innovation has emerged as a critical avenue for developing countries to capitalize on digital opportunities. This strategy not only facilitates the optimization of resource allocation in traditional industries but also propels the transformation of production methods, lifestyles, and governance approaches. Ultimately, it plays a pivotal role in fostering sustainable development. Based on an analysis of panel data encompassing 180 cities in China spanning from 2007 to 2021, this study empirically investigates the impact of MADF on GIE and its spatial spillover effect through the utilization of a multi-period double-difference model and a spatial econometric model. The findings indicate that data factor marketization plays a pivotal role in enhancing GIE, particularly in cities outside the YREB and those characterized by higher environmental regulation intensity. Mechanism analysis reveals that MADF not only directly influences GIE but also indirectly boosts efficiency by attracting FDI inflows and reducing industrial FDI. Moreover, the advancement of FinTech positively moderates the relationship between MADF and GIE. Lastly, a notable positive spatial spillover effect is observed between MADE and GIE

Based on the findings presented, we propose the following policy recommendations for consideration by China and other developing countries. First, the government should establish a multi-tiered framework for data trading and circulation to incentivize participation from both the supply and demand sides of the data factor market. By leveraging market-based allocation mechanisms, such a framework can help accelerate the realization of the economic value embedded in data resources. In addition, to unlock the value of data factors in enhancing GIE, it is essential to dismantle regional barriers, promote cross-regional data flows, and encourage the participation of multiple stakeholders—such as governments, enterprises, and individuals—to support the coordinated and efficient pursuit of multiple development objectives. For developing countries and emerging markets, it is particularly important to harness the positive contributions of high-quality FDI and advances in fintech.Additionally, enhancing the flexibility and inclusiveness of data factor market construction is essential. It is important to promote the synergistic development of data marketization and GIE tailored to local conditions. Leveraging the "second-mover advantage" and aligning strategies with urban characteristics can help unlock the potential of green innovation. Continuous stimulation of this innovation will enable data factors to effectively drive green development. In future research, we should focus on micro perspectives such as the firm level, which can better guide us to assess the impact drivers of GIE. Meanwhile, compared with the traditional linear model, we believe that the application of machine learning model can better test the optimization path of GIE. Finally, due to limitations in city-level data, we are currently unable to further distinguish the potential heterogeneous effects of vertical and horizontal FDI through institutional channels. We hope to obtain more detailed data in the future to conduct additional empirical tests.

Declaration of competing interest

The authors declare there is no conflict interest.

Data availability

Data will be made available on request.

Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

Informed consent

This article does not contain any studies with human participants performed by any of the authors.

CRediT authorship contribution statement

Conceptualization and methodology, Zhao. Z; software, Zhao. Z and Zheng. Y; validation and formal analysis, Zhao. Z and Zheng. Y; investigation and resources, Huang. J and Yan. H; data curation, Zhao. Z; writing—original draft preparation, Zhao. Z and Zheng.Y; writing—review and editing, Zhao. Z and Zheng. Y; visualization, Huang. J and Yan. H; supervision, Huang. J and Yan. H; project administration, Huang. J; funding acquisition, Zhao. Z. All authors have read and agreed to the published version of the manuscript.

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