

Data Elements Marketization and Digital Technology Innovation - Mechanism Analysis and Spatial Spillover Effects

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Abstract:

The digital technology innovation is important to the new quality productivity. Fully unleashing the value of data elements can greatly promote digital technology innovation. Therefore, this study uses China's data trading platforms to evaluate data elements marketization and explore its mechanisms and spatial effects on urban digital technology innovation. The research uses the progressive difference-in-difference method to find that the data elements marketization can significantly improve urban digital technology innovation, and through a series of tests, the results are still robust. Data elements marketization promotes it by optimizing the digital industry environment and gathering digital talents. Heterogeneity analysis finds that these effects are more pronounced in eastern cities, higher administrative levels, higher levels of intellectual property protection, and non-resource-based cities. Finally, data elements marketization has substantial spatial effects, driving digital technology innovation in relevant cities. This study offers valuable perspectives for improving data elements marketization and promoting urban digital technology innovation.

Keywords

Data Elements Marketization, Digital Technology Innovation, Digital Industry Environment, Digital Talent Agglomeration, Spatial Spillover, Difference-In-Differences Model

1. Introduction

As early as 2019, data was officially recognized as one of the key production factors, highlighting its increasingly important core role in improving production efficiency and establishing its position as the cornerstone of the modern era. As the fundamental component supporting digital technology's implementation and advancement, data brings unprecedented possibilities for urban digital technology innovation with its unique permeability and integration ability. Digital technology innovation driven by data elements can break through the shackles of the traditional innovation paradigm (Fang and Liu, 2024) [1], especially emphasizing its inherent new breakthroughs, new transformations and subversive potential (Christensen & Bower, 1996; Bogers et al., 2021) [2][3]. Digital technology innovation is demonstrating the potential to replace other forms of innovation and emerge as a new engine driving economic growth. However, at present, China's digital technology

innovation faces tangible challenges such as severe data silos, high levels of data opacity, ambiguous data ownership, and uneven resource allocation (Wang & Zhan, 2025) [4]. In general, its development still shows the characteristics of rough rather than intensive, broad but not refined, fast but not excellent, and the core technology in the digital field still holds great potential for development.

In order to meet the above challenges, clarify the ownership of data property rights, and break the data island, China has launched a special action focusing on “data elements × scientific and technological innovation”. This marks that China has officially integrated data elements into the core pillar of the national scientific and technological innovation system, providing an institutional guarantee for promoting digital technology innovation. The development of the marketization of data elements is inevitable in the market economy (Koutroumpis et al., 2020) [5]. Through data trading activities, data elements can be effectively allocated to relevant production departments and promote innovative breakthroughs in digital technology. Since 2014, China has successively established a series of data trading platforms. These platforms reflect data elements marketization and play a key role in promoting data transactions, improving data value, and promoting digital technology innovation.

Scholars' research on data elements marketization mainly focuses on two aspects: first, the measurement of data elements marketization. Most of the current research adopts a comprehensive measurement index system or uses a data trading platform to measure. Second, examine the value release of data elements marketization. The current research mainly focuses on its macroeconomic effects, such as the impact on urban green growth (Dong et al., 2025) [6], the impact on urban new quality productivity (Luo et al., 2025) [7], and the impact on urban green all-factor productivity (Pen G et al., 2025) [8]. The research on digital technology innovation is mainly carried out from two perspectives: influencing factors and economic effects. First of all, the study investigated the role of ESG (Hao et al., 2024) [9], science and technology financial policy (Shao et al., 2025) [10] and intellectual property protection in promoting digital technology innovation (Chen & Wang, 2025) [11]. Secondly, this study discusses the improvement of digital technology innovation on enterprise performance (Zhu et al., 2026) [12], enterprise investment (Lai et al., 2025) [13], enterprise resilience (Zhu et al., 2024) [14] and cities The impact of energy efficiency (Xiao et al., 2025) [15].

The existing literature research provides rich theoretical support for this study. However, few studies have examined the value release of data elements in the context of digital technology innovation. Moreover, most of the existing research is concentrated at the enterprise level. Research on digital innovation based on the perspective of cities, especially on the intrinsic mechanism and spatial effects of data elements marketization, is still rare. So, how can data elements marketization promote the level of urban digital technology innovation? Will it have a spatial spillover effect on the level of digital technology in relevant cities? How can cities solve the dilemma of digital technology innovation? The scientific answer to these questions can comprehensively and systematically reveal the mechanism and effect of data elements marketization on the innovation of urban digital technology, and provide a reference basis for deepening market-oriented reform and promoting urban digital technology innovation.

This research may make the following contributions: (1) From the perspective of urban research, use the quasi-natural experiment of establishing a data trading

platform to study the impact of data elements marketization on digital technology innovation. (2) The mechanism of data elements marketization to promote urban digital technology innovation is discussed from both theoretical and empirical perspectives, revealing its spatial spillover effect and deepening the understanding of the formation of urban digital technology collaborative innovation. (3) By examining how urban location, urban level, intellectual property protection and traditional resource endowment produce heterogeneous effects, this study provides valuable guidance for the implementation of differentiated data element market-oriented development methods.

The following sections are arranged as follows: the second section is a theoretical analysis; the third section explains the empirical model and data sources; the fourth section is the main findings of empirical research; the fifth section is an extended analysis of the spatial spillover effect; and the sixth section is the conclusion and policy suggestions.

2. Research Hypotheses

Data elements marketization can take advantage of its characteristics to eliminate regional and hierarchical data barriers and industry monopolies (Jones & Tonetti, 2020) [16]. Through the dual effects of “factorization” and “marketization”, it makes it possible to integrate data elements with production processes, eliminating digital technical barriers (Wang & Yang, 2025) [17]. At the same time, it provides institutional guarantees by improving data trading rules, thereby stimulating digital innovation vitality (Du et al., 2025) [18]. So, through which channels do it have an indirect impact on urban digital technology innovation? Can it affect digital innovation in related cities through spatial spillover effects? This paper argues that data elements marketization can affect the level of urban digital innovation by optimizing the digital industry environment and gathering digital talents. At the same time, the spatial spillover effect is used to promote the digital technology innovation of relevant cities.

In the process of data elements marketization, the data trading platform is not only a hub connecting urban data resources, but also effectively eliminates information barriers and data islands between cities (Bozkurt et al., 2023) [19]. They allow information to be transmitted between organizations and industries and build collaborative networks to promote the development of the sharing economy. The established network system has attracted emerging enterprises to establish operations and scale up in pilot cities (Liu & Ma, 2025) [20]. This enables these enterprises to identify upstream and downstream partners in the industrial chain, and gradually form a cluster effect centered on the digital industry. At the same time, the market-oriented development of data elements gives priority to cultivating and expanding digital services (Zhao et al., 2024) [21], creating a strong support for digital enterprises to enter the market. The optimized digital industry environment further guarantees urban technological innovation (Lu et al., 2024) [22]. It also reduces the cost of information search in the R & D stage of digital technology innovation, and effectively promotes more extensive and complex innovation in this field. Optimizing the digital industry environment can effectively promote the development of urban digital industry cluster. This in turn forces enterprises to continuously increase investment in innovation and enhance innovation capabilities. Therefore, this study proposes the following hypothesis:

H1: Data elements marketization can promote urban digital technology innovation by optimizing the digital industry environment.

Data elements marketization promotes multi-sector market transactions through data trading platforms and becomes a bridge for the circulation of data resources. This has promoted the digital transformation of traditional industries and the development of the big data industry, thus changing the demand of the labor market and attracting digital talents with data processing, analysis and mining capabilities (Song & Xu, 2025) [23]. Focusing on attracting and cultivating digital talents, the policy support, resource allocation and training system should be reconstructed to match the scale of digital talents with the degree of data elements marketization. The gathering of digital talents enables the rapid circulation and sharing of professional knowledge, experience and data resources necessary for digital technology innovation. This reduces the cost of information transmission, promotes the collision and integration of interdisciplinary knowledge, and significantly improves the quality and efficiency of R & D (Li et al., 2022) [24]. At the same time, it expands the market scale of digital technology innovation products and enriches its coverage and application scenarios. The resulting economic benefits will generate a strong driving force for innovation and attract more digital technology innovations. This really maximizes the role of knowledge exchange, greatly reduces the opportunities for digital technology innovation to be blocked, and improves the overall level of innovation. Therefore, this study proposes the following hypothesis:

H2: Data elements marketization can promote urban digital technology innovation by strengthening digital talent agglomeration.

Data elements marketization basically has the characteristics of “market-driven”, that is, its scope of activities and resource allocation will naturally break through the traditional geographical boundaries. The externality hypothesis believes that the data trading platform presents the characteristics of public goods, thus producing significant externality (Ichihashi, 2021) [25]. In a fully self-regulated market, it is difficult to fully consider these extensive external influences. Therefore, some public sector projects, such as the creation of data trading platforms, data infrastructure and data governance frameworks, are crucial to guiding market participants. By establishing an effective external internalization system, these government actions have formed and expanded the beneficial effects of the market. The resulting economic externalities go beyond local areas and extend to a larger economy and society (Yan et al., 2025) [26]. That is to say, data elements marketization can break down data barriers, promote cross-regional circulation (Fernandez et al., 2020) [27], overcome the spatial constraints of traditional innovation, accelerate the diffusion of knowledge and technology, and give full play to the multiplier effect of data elements, so as to generate the surrounding areas Digital technology innovation overflows (Li Wei, 2024) [28].

H3: Data elements marketization can affect the digital technology innovation of adjacent cities through a spatial spillover effect.

3. Research Design

3.1. Model construction

The benchmark regression model is shown in Equation (1):

$$\text{Diginnov}_{it} = \alpha_0 + \alpha_1 \text{DID}_{it} + \alpha_n \text{Controls}_{it} + \mu_i + \varphi_t + \varepsilon_{it} \quad (1)$$

$Diginnov_{it}$ is digital technology innovation in city i during year t , DID_{it} is the policy dummy variable for city i in year t , $Controls_{it}$ is the set of all control variables, μ_i indicates city fixed effect for i , φ_t is time fixed effect, and ε_{it} is the random disturbance term. Furthermore, α_1 represents the regression coefficient of primary interest.

Subsequently, this study examines the impact mechanism of the digital industry environment and the digital talent agglomeration, and tests whether they are mechanism variables. On the basis of equation (1), we built a model (2) to test, focusing on the impact of the core explanatory variable on the mechanism variable (M).

$$M_{it} = \beta_0 + \beta_1 DID_{it} + \beta_n Controls_{it} + \mu_i + \varphi_t + \varepsilon_{it} \quad (2)$$

A spatial model is specified to examine spatial spillover effects, formulated as follows:

$$Diginnov_{it} = \delta_0 + \rho W \times Diginnov_{it} + \delta_1 DID_{it} + \delta_2 W \times DID_{it} + \delta_3 Controls_{it} + \delta_4 W \times Controls_{it} + \mu_i + \varphi_t + \varepsilon_{it} \quad (3)$$

W represents the spatial weight matrix, including both adjacency matrix and economic geography weight matrix. ρ denotes the spatial autoregressive coefficient of urban digital technology innovation. We employ two different spatial matrices and two different spatial model regressions to enhance the robustness.

3.2. Variable and description

Since utility model patents in the digital economy focus on product form and external modifications rather than disruptive innovations. The quantity of invention patent applications is especially used in this study to gauge a city's yearly output of digital technology innovation. Digital technology innovation is assessed by the quantity of invention patent applications per 100 people in digital economy.

Construct dummy variables based on the year of whether the city has built a data trading platform, which is used as an agent indicator to explain data elements marketization (DID): when a city starts construct a data trading platform, the value is 1; otherwise, the value is 0.

Digital industry environment: In accordance with the research method of Liu and Ma (2025) [20], the study assesses the digital industry environment by the proportion of new information transmission, software and information technology service industry and scientific research and technology service enterprises to overall total of new enterprises for that year within each city.

Digital talent aggregation intensity: The study follows the method used by Huang et al. (2023) [29], utilizing the locational entropy index to measure digital talent aggregation intensity. The specific equation is as follows:

$$dig-agg = \sum_i (ve_{it}/e_{it}) / (ve/e) \quad (4)$$

Where ve_{it} denotes the number of individuals employed in the information transmission, computer services, and software industry, as well as the scientific research, technical services, and geological exploration industry in city i during year t . e_{it} represents the total employment in city i during year t . ve indicates the national employment figures for the aforementioned industries in year t . e signifies the national total employment during year t .

The control variables selected in this study: (1) economic development (lnagdp), measured by the logarithm of per capita GDP; (2) financial development (finance), measured by the ratio of total bank loans to GDP; (3) education expenditure (education), calculated by the logarithm of education expenditure; (4) Science and technology investment (science) is measured by the logarithm of science and technology expenditure; (5) Government intervention (gov) is measured by the proportion of local government general budget expenditure to GDP; (6) marketization level (market) is measured by the proportion of total retail expenditure on social consumer goods to GDP. The descriptive statistical results are shown in Table 1.

Table 1. Summary statistics.

Variable	N	Mean	Min	Sd	Max
<i>Diginnov</i>	3679	0.019	0	0.073	1.115
<i>DID</i>	3679	0.049	0	0.217	1
<i>dig-ie</i>	3679	0.036	0.004	0.032	0.386
<i>dig-agg</i>	3679	0.919	0.001	0.933	15.734
<i>lnagdp</i>	3679	10.743	8.576	0.591	12.456
<i>finance</i>	3679	1.052	0.132	0.621	7.450
<i>education</i>	3679	13.141	9.627	0.817	16.276
<i>science</i>	3679	10.428	6.624	1.448	15.529
<i>gov</i>	3679	0.199	0.044	0.101	0.916
<i>market</i>	3679	0.379	0.049	0.108	1.013

3.3. Data sources

Due to constraints with data availability and consistency, the study omits Hong Kong, Macao, Taiwan, Xizang and any cities where substantial data gaps exist as a result of administrative adjustment. Data sources are mainly divided into three groups: (1) The digital economy patent application data is sourced from the digital economy research database of CNRDS. (2) The date and location data of the trading platforms are manually collected and sorted out by the author from the official websites. (3) The control variable data is taken from the China Urban Statistics Yearbook, the Local Statistical Yearbook, the EPS database and the websites of various provincial statistical bureau

4. Empirical Analysis

4.1. Benchmark regression analysis

To enhance the reliability of findings, this study adopts the stepwise regression method to examine regression coefficient of data elements marketization on urban digital technology innovation under different control variables. In column (1) of Table 2, under the condition that the control time and region are fixed, and only one explanatory variable is included, the regression coefficient obtained in this study is 0.050, which is Markedly positive. This shows that data elements marketization has significantly promoted the progress of urban digital technology innovation. Columns (2) to (7) After incorporating different control variables, the coefficient of marketization of data elements is still significantly positive in all cases, confirming that data elements marketization has a driving impact on urban digital technology innovation.

Table 2. Benchmark regression results.

	digital technology innovation						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>DID</i>	0.050*** (0.014)	0.050*** (0.014)	0.050*** (0.014)	0.046*** (0.013)	0.045*** (0.014)	0.044*** (0.014)	0.042*** (0.013)
<i>Lnagdp</i>		-0.003 (0.003)	-0.003 (0.003)	-0.017*** (0.005)	-0.019*** (0.006)	-0.029*** (0.007)	-0.031*** (0.007)
<i>Finance</i>			0.001 (0.003)	0.000 (0.003)	-0.000 (0.003)	0.001 (0.003)	0.002 (0.003)
<i>Education</i>				0.044*** (0.012)	0.041*** (0.012)	0.041*** (0.012)	0.041*** (0.012)
<i>Science</i>					0.003** (0.001)	0.003** (0.001)	0.003** (0.001)
<i>Gov</i>						-0.082*** (0.019)	-0.088*** (0.021)
<i>market</i>							-0.040** (0.017)
<i>_cons</i>	0.017*** (0.001)	0.051 (0.036)	0.044 (0.034)	-0.377*** (0.121)	-0.337*** (0.118)	-0.232** (0.112)	-0.183* (0.104)
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3679	3679	3679	3679	3679	3679	3679
R ²	0.887	0.887	0.887	0.892	0.892	0.893	0.894

Note: Values in parentheses indicate robust standard errors clustered at the city level. * denotes $P < 0.1$, ** denotes $P < 0.05$, *** denotes $P < 0.01$. The same applies to all tables below.

4.2. Influence mechanism analysis

Based on the results of theoretical analysis, the influence mechanism is empirically tested. The DID coefficient of the first column in Table 3 is significantly positive, indicating that data elements marketization has improved the digital industry environment. The research shows that optimizing the digital industry environment is conducive to cultivating and attracting emerging digital industries and enterprises, reducing the obstacles to cooperation and communication between related enterprises, and stimulating the vitality of digital technology innovation. Therefore, this study believes that data elements marketization promotes urban digital technology innovation by optimizing the digital industry environment, and H1 is confirmed.

The results of column (2) show that data elements marketization has significantly promoted the aggregation of digital talents, with a positive correlation coefficient of 0.585, which is statistically significant. In addition, research shows that the talent agglomeration effect reduces the cost of employee search. At the same time, digital talents have high digital technology innovation ability and willingness to innovate. Hiring these talents can improve the R&D efficiency of enterprises in digital technology innovation, so as to improve the innovation ability of urban digital technology. Therefore, this study believes that data elements marketization promotes urban digital technology innovation by gathering digital talents, and H2 is confirmed.

Table 3. Mechanism testing results.

	(1)	(2)
	M ₁	M ₂
DID	0.018*** (0.006)	0.585*** (0.203)
_cons	-0.048 (0.047)	2.860 (2.458)
Control	Yes	Yes
City FE	Yes	Yes
Year FE	Yes	Yes
N	3679	3679

4.3. Robustness tests

4.3.1. Parallel trend test

This study takes the data trading platform as the key event node, and the analysis covers the first 5 periods of the platform and the 5 periods after the platform. As shown in Figure 1, no notable differences were observed among the city groups prior to the launch of the platform. At the same time, data elements marketization has had a pronounced and continuous positive impact on the innovation of urban digital technology: the estimation coefficient of the processing group during and after the platform is significantly positive. It can be proved that the parallel trend hypothesis is true.

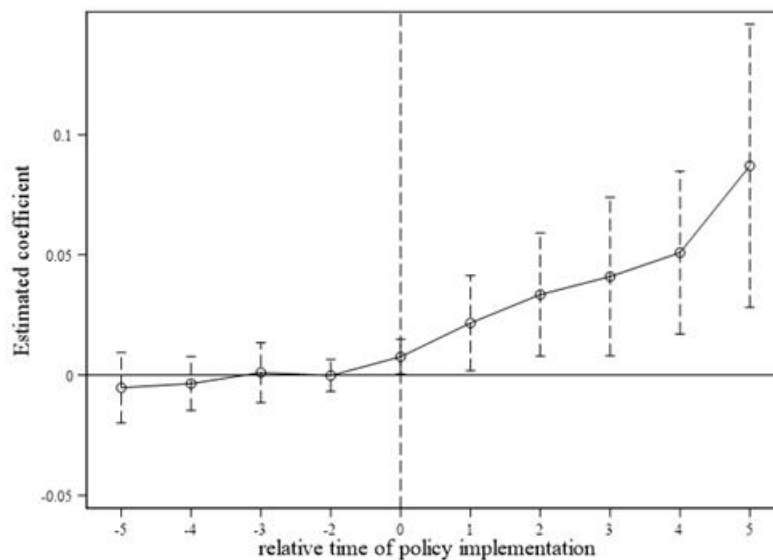


Figure 1. Parallel trend test.

4.3.2. Placebo test

In order to avoid the deviation caused by autocorrelation and missing variables, this study used a placebo test. Through 500 random samplings of the treatment group cities and the time points of influence, the sampling results were transformed into Equation (1) for regression analysis, and the kernel density distribution map of the “pseudo” estimation coefficient was obtained, as shown in Figure 2. The p-value distribution is similar to the normal distribution, and most of the values are greater than 0.1, which confirms that other random factors do not affect the empirical results.

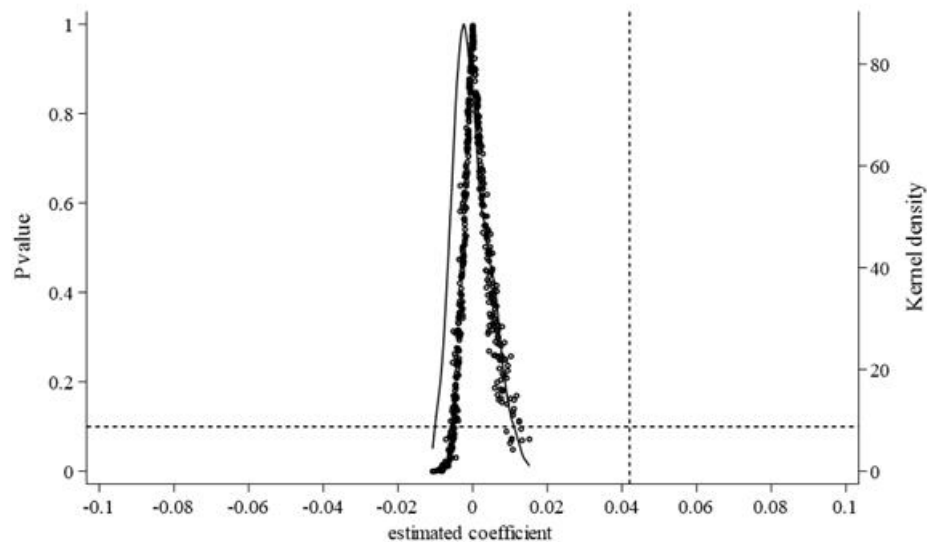


Figure 2. Placebo test.

4.3.3. PSM-DID

To reduce problem of self-selection bias, the study uses PSM-DID to check robustness. We calculated propensity scores via a logit model. Subsequently, we applied kernel matching to match observations and re-estimated Equation (1) using the matched sample. According to the findings presented in column (1) of Table 6, the coefficient has statistical significance. In order to further enhance the credibility of the research conclusions, we use the neighbour matching method and the radius matching method for analysis respectively. The DID coefficient shown in columns (2) and (3) is still significantly positive, which further verifies our main conclusion's robustness.

4.3.4. Instrumental variables estimation

With the aim to effectively solve the endogenous problems, this study selects the number of urban post offices in 1984 (IV1) and the number of fixed telephones in 1984 (IV2) as tool variables for data elements marketization. Specifically, the two-stage least squares method of instrumental variables is used to test the causal relationship between data elements marketization and the urban digital technology innovation. First of all, interaction items of IV1 and IV2 with the post variable (Post) are included in the regression respectively. In columns 1 and 2 of Table 4, the coefficient of instrumental variable in the first stage is significantly positive, which meets the relevant requirements. In the second stage, the F-statistic of the weak instrument test exceeded the 10 % reserve Yogo critical value of 16.38, confirming the exogeneity. The Kleibergen-Paap rk LM statistic is highly significant, which confirms the feasibility of identifying instrumental variables. In order to ensure robustness, columns 3 and 4 of Table 4 further incorporate the interaction between IV2 and postal variables for regression. Data elements marketization has a significant positive impact on urban digital technology innovation, which verifies the reliability of the benchmark regression results.

Table 4. Instrumental variables result.

Variable	DID	Diginnov	DID	Diginnov
DID		0.055*** (0.019)		0.060*** (0.021)
IV1×Post	0.016*** (0.002)			
IV2×Post			0.130*** (0.049)	
_cons	0.469 (0.380)		0.374 (0.352)	
Control	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	2899	2899	2899	2899
F statistic	86.383***		49.080***	
LM statistic	32.879***		33.314***	

4.3.5. Heterogeneity treatment effect

In the process of did, due to the difference in treatment timing, the group receiving the new treatment may set the group receiving the previous treatment as the control group, resulting in a negative weight problem, resulting in a deviation in the final estimated coefficient. In order to solve this problem, we use the method proposed by Goodman Bacon (2021) [30] to evaluate the deviation of the results. As shown in Table 5, the weight of “T vs Never T” was the largest in all three groups, reaching 96.8%. In addition, the estimated coefficient of this group is closest to the benchmark regression coefficient. This shows that the observed processing group effect is caused by data elements marketization driven by data trading platforms, rather than the improvement of urban digital technology innovation level caused by the difference in processing timing.

Table 5. Bacon decomposition results.

Group	Digital Technology Innovation	
	Weight	Estimated coefficient
Early T vs Late C	0.020	0.023
Late T vs Early C	0.012	-0.047
T vs Never T	0.968	0.051

Note: C is the control group, T is the treatment group.

In addition, in order to eliminate the impact of inconsistent implementation time on the results, this study implements a superimposed DID model. As shown in Figure 3, after considering the treatment heterogeneity, the parallel trend hypothesis of the two groups is still satisfied before the data trading platform is established. After the establishment of the platform, the estimated DID coefficient of the treatment group still increased significantly. This indicates that the results remain robust.

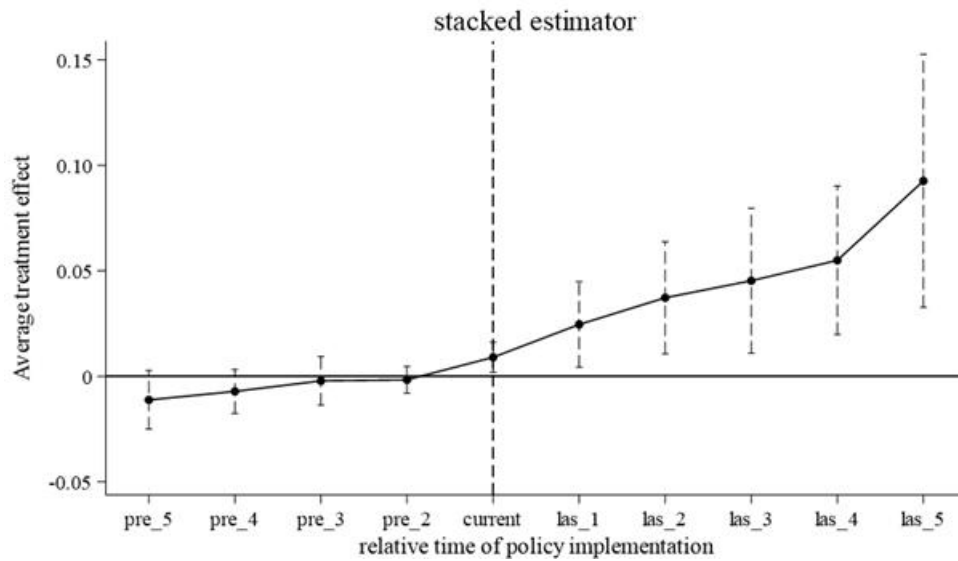


Figure 3. Test for heterogeneous treatment effect.

4.3.6. Other robustness tests

(1) Eliminating the central city to regress. After excluding four municipalities directly under the central government, this study conducted regression analysis again. As displayed in column 4 of Table 6, the coefficient remains significant at the level of 1%, and the direction remains unchanged, which indicates that data elements marketization can indeed improve urban digital technology innovation, and also verifies the validity of the benchmark regression conclusion. (2) Replacing the dependent variable. This study replaces it with the actual number of authorized patents per capita, which can more accurately reflect the innovation output. After substituting the new dependent variables into Equation (1) for re-analysis, the column (5) of Table 6 shows that the core coefficient is still significantly positive, which provides a strong support for the reliability of the regression results. (3) Eliminating competitive policy interference. During the sample period, China has implemented some policies related to digital technology innovation, which may interfere with the research results. The “Broadband China” pilot policy in 2014 aims to strengthen digital infrastructure as a solid foundation for digital technology innovation and was implemented in 2015 and 2016. In addition, in 2012, 2013 and 2014, the country has launched three waves of smart city construction, vigorously promoting digital technology innovation with the help of artificial intelligence, and comprehensively improving urban efficiency. The policy of the National Big Data Comprehensive Experimental Zone in 2015 aims to promote China’s big data innovation. These three policy categories are highly relevant to this study. Therefore, the benchmark regression model contains dummy variables indicating whether a city is included in the “Broadband China” pilot, smart city construction or national big data comprehensive pilot area policy in the corresponding year. Table 7 shows that once the three mitigation policies are discounted, the DID regression coefficient is still positive. This reinforces the findings of the study because of their position.

Table 6. Robustness test.

	Kernel density matching	Radius matching	Nearest neighbour matching	Eliminating the central citys	Replace dependent variable
DID	0.038*** (0.013)	0.035*** (0.012)	0.035*** (0.012)	0.031*** (0.010)	0.016*** (0.005)
_cons	-0.169 (0.132)	-0.151 (0.124)	-0.151 (0.124)	-0.215** (0.103)	-0.088* (0.048)
Control	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	3127	3108	3108	3627	3679
R ²	0.896	0.899	0.899	0.906	0.843

Table 7. Exclusion of competitive hypotheses.

Variable	Digital Technology Innovation		
	Exclusion of Broadband China Pilot	Exclusion of Smart City Pilot	Exclude Big Data Comprehensive Pilot Zones
DID	0.041*** (0.013)	0.042*** (0.013)	0.041*** (0.013)
Broadband China	0.013*** (0.005)		
Smart Cities		-0.002 (0.003)	
National Big Data Comprehensive Pilot Zone			0.017* (0.009)
_cons	-0.224** (0.104)	-0.182* (0.103)	-0.278** (0.120)
Control	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	3679	3679	3679
R ²	0.896	0.896	0.894

4.4. Heterogeneity analysis

4.4.1. Analysis of the heterogeneity of urban geographical location

Geographical factors make a key influence on the differences in regional digital innovation resource acquisition, which is mainly due to regional differences in the data trading platforms and the flow of data elements. To explore this phenomenon, this study constructs a dummy variable, assigns the value of eastern cities to 1 and other regions to 0, and incorporates the dummy-DID interplay in modified Equation (1). Consistent with the baseline regression result, column (1) of Table 8 shows that the coefficient of the interaction is significantly positive. This shows that the impact of data elements marketization on digital technology innovation is more explanatory in the eastern region. Eastern cities usually have a more diversified economic base, which can better meet the needs of the digital revolution. Under these conditions, the establishment of a perfect data exchange mechanism can create more possibilities for technological progress in the digital field.

4.4.2. Analysis of the heterogeneity of urban hierarchical structure

The administrative level of the city will affect the distribution of urban data resources and data elements marketization. Therefore, this study classifies sample cities according to their administrative status. High-level cities include municipalities directly under the Central Government, provincial capital cities and sub-provincial cities, while the rest of the cities are general cities. This study introduces virtual variables. The value distribution of high-level cities is 1, and the value distribution of general cities is 0. Column (2) shows the estimated results. The interaction coefficient is positive, and the statistics are significant, which is consistent with the results of the benchmark regression. This shows that data elements marketization has a more significant impact on digital technology innovation in high-level cities than in general cities. A reasonable explanation is that ordinary cities face structural constraints, are highly dependent on traditional industries, have a low degree of industrial digitalization, and it is difficult to deeply integrate data elements with the real economy. In addition, its innovation ecosystem is relatively weak, which is manifested in the weak cooperation mechanism between industry, academia and the imperfect data property rights and transaction system. These factors prevent them from fully obtaining the innovation dividends brought by data elements marketization, so the promotion effect is relatively limited.

4.4.3. Analysis of the heterogeneity of intellectual property protection

The number of digital patents developed by different cities is affected by intellectual property protection. This study classifies sample cities according to their level of intellectual property protection, assigns cities with strong intellectual property protection to 1 and other cities to 0, and explores whether there is a difference in the impact of data elements marketization on the progress of digital technology under different intellectual property protection conditions. Column (3) shows positive and statistically significant interactions. This shows that the higher the degree of intellectual property protection in cities, the greater the benefit of marketization of data elements. Cities with relatively perfect incentive mechanisms and clear definitions of property rights tend to have higher intellectual property protection, which can encourage innovation entities to use the value generated by data elements marketization to promote digital technology innovation.

4.4.4. Analysis of the heterogeneity of traditional resource endowment

The resource endowment of the city provides resource conditions for digital technology innovation. In order to measure the difference caused by it, this study divides the sample: resource-dependent cities are assigned to 1, and conversely, assigned to 0. According to the column (4) of Table 8, the coefficient is -0.048, showing a statistically significant negative correlation. This shows that for resource-based cities, data elements marketization has not produced the expected results in promoting digital innovation. This may be because the excessive dependence on natural resources that plagues these cities often leads to a lack of investment innovation, a loss of top talent, insufficient development of digital infrastructure, and impedes the ability to upgrade industries that need to be focused. Therefore, there are technical obstacles to the integration of data elements and traditional sectors, which hinder the release of data elements' value and digital technology innovation.

Table 8. *Heterogeneity test.*

Classification method	Eastern cities (1)	Major metropolitan (2)	High intellectual property protection cities (3)	Resource-based cities (4)
DID × location	0.062** (0.025)			
DID×level		0.060*** (0.019)		
DID×protection			0.063*** (0.019)	
DID×resource				−0.048*** (0.015)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	3679	3679	3679	3679
R ²	0.898	0.897	0.898	0.895

5. Further Analysis: Spatial Spillover Effects

This study first uses a widely utilized adjacency matrix as the spatial weighting matrix in order to investigate whether data elements marketization can produce geographical spillover effects on urban digital technology innovation. As illustrated in Table 9, the spatiotemporal Bidirectional Fixed Spatial Durbin Model (SDM) is finally chosen after a series of LM, LR, Wald, and Hausman tests. Nevertheless, information and economic connections between non-adjacent locations are frequently severed by adjacency matrices. To put the matrix findings to the test and ensure they're reliable, this study brings an economic geography weight matrix into the mix—one that captures both the market-driven and transactional sides of how data elements get commercialized. In addition, we also show the estimated results with double fixed effects to effectively test the robustness of our research conclusions.

Table 9. *Global Moran's I for urban digital technology innovation.*

Year	Moran's I	Z	P
2010	0.101	7.207	0.000
2011	0.089	5.630	0.000
2012	0.165	8.393	0.000
2013	0.192	7.710	0.000
2014	0.214	7.728	0.000
2015	0.321	10.479	0.000
2016	0.348	11.259	0.000
2017	0.392	12.026	0.000
2018	0.357	10.757	0.000
2019	0.299	8.873	0.000
2020	0.286	8.291	0.000
2021	0.241	6.978	0.000
2022	0.199	5.669	0.000

Table 9 clearly illustrates that, under the adjacency matrix, the Moran's I index of digital technology innovation across Chinese cities from 2010 to 2022 reveals a strikingly positive link. This reveals that during this period, there is a significant spatial auto-correlation in Chinese cities, and there is a trend of clustering.

It can be seen from Table 10 that the spatial autoregression coefficient in SDM and the spatial interaction coefficient of data elements marketization are both significantly positive. This shows that in the process of marketization of data elements, cities not only have an endogenous space overflow effect, but also have exogenous space interaction. The spatial autoregression coefficient is positive, indicating that there is a strong correlation between local digital technology innovation and relevant urban digital technology innovation. Data elements marketization forms a chain reaction through indirect influence, which has played a significant role in promoting digital technology innovation in surrounding cities. That is to say, while promoting local digital technology innovation, data elements marketization has also promoted the digital technology innovation of relevant cities, thus enhancing the overall digital technology innovation effect of data elements marketization. Therefore, our third hypothesis has been verified.

Table 10. Spatial model regression results.

Model	SDM		SAR	
Spatial matrix	Adjacency matrix	Economic geography weight matrix	Adjacency matrix	Economic geography Weight matrix
ρ	0.385*** (0.021)	0.719*** (0.022)	0.409*** (0.020)	0.764*** (0.019)
DID	0.038*** (0.003)	0.029*** (0.002)	0.038*** (0.003)	0.031*** (0.002)
W× DID	0.019*** (0.005)	0.014** (0.007)		
Direct influence	0.041*** (0.003)	0.034*** (0.003)	0.040*** (0.003)	0.035*** (0.003)
Indirect influence	0.050*** (0.007)	0.117*** (0.023)	0.024*** (0.002)	0.098*** (0.012)
Total influence	0.092*** (0.008)	0.151*** (0.024)	0.064*** (0.005)	0.134*** (0.014)
Control	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	3679	3679	3679	3679

6. Conclusions and Policy Implications

This study takes the construction of the data trading platform as a quasi-natural experiment. Using the panel data of 283 cities from 2010 to 2022, the progressive double difference model was used to systematically analyze the digital technology innovation effect of data elements marketization. Including the driving mechanism, impact effect and spatial characteristics of data elements marketization on urban digital technology innovation. The main research results are as follows: through the robustness test, the empirical evidence is fully confirmed. Data elements marketization has significantly promoted the innovation of urban digital technology. Further heterogeneity analysis shows that cities in the eastern region with perfect intellectual property protection, high administrative management level and economic non-resource dependence are more significantly affected by data elements marketization. Third, data elements marketization has opened up a diversified path for urban digital technology innovation by optimizing the digital industry environment and strengthening the gathering of digital talents. Fourth, it is further verified that the impact of data elements marketization on urban digital technology innovation has a spatial spillover effect, which shows that data elements marketization is conducive to

building a new pattern of coordinated development of cross-regional digital innovation.

Based on the empirical research results, this article puts forward the following policy suggestions. First, continue to refine data elements marketization. Cities should establish a data trading platform to fully unleash the vitality of the data element market. This requires optimizing the top-level design framework and formulating a unified and secure transaction rule system. Comprehensive planning should be carried out in the whole process of data ownership recognition, circulation and transaction, income distribution, and data element security management. By ensuring the effective coordination of all stages, we can better realize the digital technology innovation effect driven by the marketization of data meta.

Second, vigorously promote the differentiated reform of data elements marketization. Data elements marketization must adhere to the concept of local adaptation and precise policies. Big cities and high-level cities should give priority to the establishment of a perfect data exchange mechanism, and central and western cities and low-level administrative units should set up special funds to focus on cultivating data resource development capabilities. Cities with weak intellectual property protection need to strengthen the construction of patent protection systems to create good soil for digital technology innovation.

Third, actively explore the diversified path of promoting digital technology innovation through data elements marketization. Municipal departments should focus on cultivating the ecology of local digital enterprises, attract new market entities to enter, and guide the success of digital transformation projects through strategic investment incentives. By providing housing support policies that match R&D investment and allowing top digital experts to practice across platforms, digital talent clusters can be effectively gathered.

Fourth, build a regional innovation and collaborative governance mechanism for digital technology. Relevant departments should pay attention to promoting the cooperation of digital technology innovation between cities and establish a digital innovation community across administrative regions. Formulate a data flow element plan based on the metropolitan area, establish a circulation negative list system, and promote the marketization of data meta from the three levels of top-level design, middle-level planning and bottom-level implementation. By strengthening the cooperation in the construction of regional data exchange hubs, improving the income distribution mode of cross-jurisdiction data transactions, and optimizing the comprehensive utilization of urban digital innovation advantages and resources, the market-oriented operation efficiency of data elements can be significantly improved.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this article.

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