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Research on the Promotion Effect of the Marketization of Data Elements on the Digital Transformation of Manufacturing Enterprises: An Empirical Evaluation of a Multiperiod DID Model

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Abstract: The marketization of data elements is a critical step in harnessing the potential of data as a "new" economic element. This process is essential for driving the digital transformation of manufacturing enterprises and achieving sustainable development. Using data from listed manufacturing enterprises (2013–2022), this study applied the difference-in-differences method to analyze how the marketization of data elements accelerates digital transformation. The results indicated that data trading platforms play a significant role by lowering enterprise costs, easing financing constraints, fostering digital technology innovation, and promoting the growth of the digital service industry. The impact varies across regions, ownership structures, and executive backgrounds. This research offers fresh insights into facilitating the digital transformation of manufacturing enterprises and provides practical guidance for policymakers to advance the market-oriented reform of data elements and enhance enterprises' digital capabilities.

Keywords: the marketization of data elements; enterprise digital transformation; manufacturing enterprises; differences-in-differences; digital economy

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1. Introduction

In the era of the digital economy, the rapid expansion and large-scale application of data have positioned data as a fundamental economic resource and key production factor [1]. Recent advancements in data-driven technologies demonstrate substantial potential in overcoming industrial challenges, further reinforcing the necessity of digital transformation for manufacturing enterprises [2]. This transformation is essential to enhance competitiveness, improve overall economic efficiency, and promote sustainable development [3]. However, manufacturing enterprises face persistent challenges, such as data silos and security concerns, that impede their capacity to effectively utilize data for innovation and operational optimization. As a cornerstone of the national economy, the manufacturing sector must navigate these obstacles to successfully undergo digital transformation in this data-driven era.

To address the challenges associated with the digital transformation of manufacturing enterprises, scholars have explored various digitalization pathways from technological, organizational, and environmental perspectives. Li et al. (2024) integrated knowledge graphs with OPC UA information models to enhance interoperability and data integration in industrial environments [4]. Zhang et al. proposed a generalized framework for secure

federated domains authorized by blockchain, which enhances secure data sharing in distributed environments, thereby protecting data privacy while facilitating collaborative model training [5]. Svahn et al. (2017) suggested overcoming digital barriers by establishing dedicated digital transformation departments, which strengthen firms' capacity for data integration and utilization [6]. Additionally, scholars have emphasized the importance of accelerating digital infrastructure development to provide cost-effective data storage and transmission solutions, thus reducing entry barriers to digital adoption for manufacturing enterprises [7,8]. Currently, most research focuses on data-related challenges within specific domains, such as data circulation and security. As an integrated governance mechanism, the data element market addresses this systemic issue through integrated, multidimensional services. However, limited studies have examined the intrinsic relationship between the marketization of data elements and the digital transformation of manufacturing enterprises.

The marketization of data elements is crucial for creating an environment conducive to digital transformation and accelerating this process within enterprises. By establishing data trading platforms, marketization facilitates the optimal allocation and value realization of data resources, thereby promoting the sustainable development of manufacturing enterprises [9]. Given the accelerating wave of digitization worldwide, it is imperative to investigate how the marketization of data elements can propel the digital transformation of manufacturing enterprises. This study employed a quasinatural experiment approach wherein the establishment of a data trading platform functioned as a quasinatural experimental setting. An empirical analysis was conducted using the difference-in-differences (DID) method to address the following research questions: does the marketization of data elements facilitate the digital transformation of manufacturing enterprises, and what are the underlying mechanisms of influence of this marketization? The findings contribute to the theoretical framework of the marketization of data elements and provide practical insights into overcoming digital transformation challenges in manufacturing enterprises. Furthermore, these insights collectively support sustainable economic and social development at both macroeconomic and microeconomic levels.

The potential marginal contribution of this study is twofold. First, it provides micro-level evidence concerning the role of data factor markets in value creation. This study focuses on manufacturing enterprises, analyzing the impact mechanisms of the marketization of data elements on their digital transformation from both enterprise-level and city-level perspectives. It provides a more comprehensive understanding of the micro-level dynamics of the data element market. Second, it extends current findings on the influence of antecedent policy factors on the outcomes of digital transformation in manufacturing firms. During the digital transformation process, manufacturing enterprises often depend on external resources while facing considerable challenges. Therefore, it is essential to investigate the role of an emerging external factor, specifically the marketization of data elements, in driving the digital transformation of manufacturing enterprises. This exploration is crucial for comprehending and advancing digital transformation within these enterprises.

2. Policy Background and Theoretical Analysis

2.1. Policy Background

Since the Fourth Plenary Session of the 19th Central Committee of the Communist Party of China (CPC) first recognized data as a factor of production in 2019, their strategic significance has risen to an unprecedented level at the national scale. As a new type of production factor, data—along with the reform of their market-based allocation—have become a key driver of high-quality economic development. To accelerate the secure circulation and innovative utilization of data elements, unlock latent data element resources, and maximize their value, China has implemented foundational systems and policies to

systematically promote the development of a market-oriented data element system. A key component of this initiative is the establishment of data trading platforms, which serve as practical exemplars. China's data trading platforms emerged in 2014 as a key initiative to advance the marketization of data elements. Between 2014 and 2017, approximately 20 data trading platforms were established, including the Zhongguancun Big Data Trading Platform and the Guiyang Big Data Exchange. However, this process encountered challenges, including platform inactivity and frequent market disorder. This phase is referred to as the "brokering" stage [10]. Between 2018 and 2020, the development of data trading platforms stagnated, leading to a year-on-year decline in their number. This decline can be attributed to multiple factors, including insufficient integrated planning, inadequate infrastructure, and challenges in realizing data assetization. After 2021, data trading platforms entered their 2.0 era, characterized by mature development and the establishment of platforms in major cities such as Beijing, Shanghai, and Shenzhen. As of September 2024, more than 50 government-led data trading platforms have been established nationwide, forming a multitiered data element market system centered around the national data trading platform. The number of data trading platforms established in recent years is shown in Figure 1.

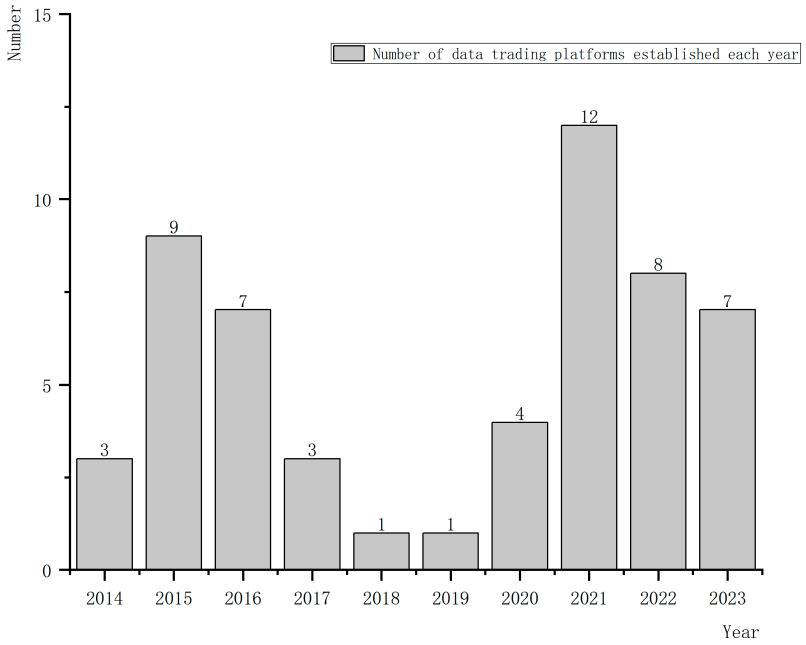


Figure 1. The number of data trading platforms established in China from 2014 to 2023.

2.2. Theoretical Analysis and Research Hypotheses

Building on previous research and theoretical analysis, this paper proposes five hypotheses, as illustrated in Figure 2. The figure depicts both the direct and indirect impact pathways through which the marketization of data elements influences the digital transformation of manufacturing enterprises. The arrows indicate the direction of influence between variables.

The establishment and operation of a data trading platform are essential for enabling enterprises to exchange information, facilitate knowledge transfer, and enhance the market-oriented utilization of enterprise information assets [11]. The data element market provides a robust platform for the effective aggregation of data resources, allowing manufacturing enterprises to streamline the acquisition of high-quality data. This empowers these enterprises to undergo transformation and innovation through the utilization of digital capabilities [12]. By leveraging more effective data analysis and mining techniques, organizations can achieve optimized decision-making processes, thereby significantly enhancing

productivity and innovation within the manufacturing sector. Furthermore, the marketization of data elements promotes the optimization of enterprise resource allocation and improves efficiency through synergistic interactions among various factors. Replicable and noncompetitive data elements are gradually replacing traditional production inputs. This transition will optimize the structure of production elements and enhance marginal productivity, leveraging their cost advantages over conventional production resources [13]. Specifically, data elements play a crucial role in providing comprehensive market insights, optimizing the decision-making process, enhancing supply chain management, and ensuring accurate human resource allocation. These capabilities collectively enable other production factors—such as capital, labor, and technology—to achieve efficient resource allocation and maximize value [14]. In addition, the marketization of data elements facilitates the dismantling of information barriers across regions and levels. While this development provides abundant and transparent data resources, competition among enterprises has intensified. Consequently, companies must expedite their digital transformation efforts to sustain their competitive advantage, thereby enhancing their responsiveness and market sensitivity. This leads us to the statement of Hypothesis 1:

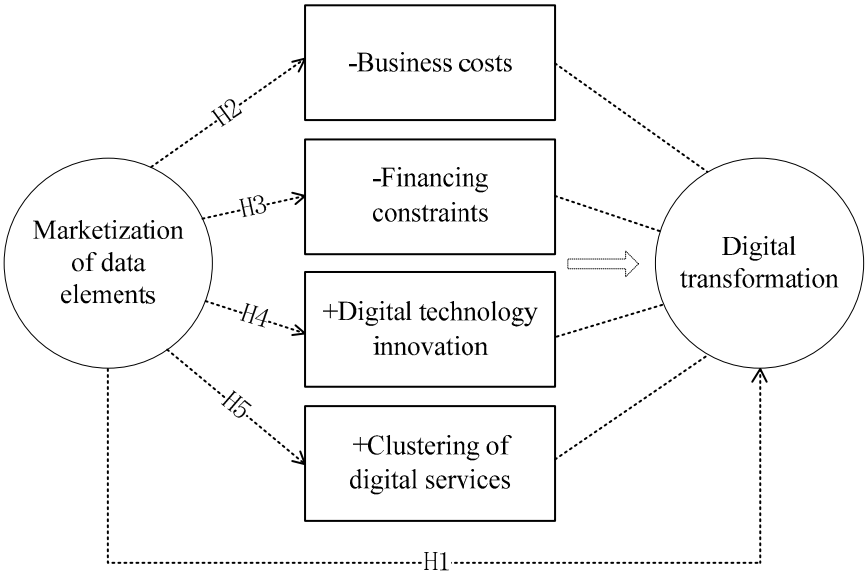


Figure 2. Theoretical analysis and research hypotheses.

H1: *The marketization of data elements can enhance the digital transformation of manufacturing enterprises.*

The digital transformation of manufacturing enterprises requires substantial initial investments, including investments in technology, talent development, process transformation, and effective risk management. These investments not only increase operational costs but heighten the risk-bearing pressure during the transformation process. As companies are expected to independently shoulder the costs and potential losses associated with the transformation, high operational costs may undermine their ability to manage risks and reduce their willingness to pursue digital transformation. In this context, the marketization of data elements provides abundant informational resources. It helps decision-makers identify patterns, trends, and correlations, offering deep insights into business operations. This enables rapid adjustments to production and marketing strategies. This decision optimization can help minimize costs caused by erroneous decisions, improve resource allocation efficiency, and reduce management costs. Moreover, the substantial resource investment and transformation risks highlight the growing need for manufacturing en-

terprises to pursue collaborative efforts during digital transformation in order to mitigate potential transformation costs [15]. The data element market serves as a platform for collaborative innovation among enterprises, facilitating the flow and spillover of innovative knowledge across different entities. It enables enterprises to form complementary advantages in data resources, market information, and innovation strategies, empowering them to make precise decisions and predict risks based on data analysis [16]. For example, General Electric's (GE) Predix platform, a globally renowned industrial solution, integrates operational data from industrial equipment to provide businesses with precise data services. This helps them quickly identify optimization opportunities in production processes, which not only reduces data acquisition costs but offers reliable support for optimizing production workflows [17]. Additionally, by innovating the economic system and fostering market transaction habits, market-oriented reforms effectively reduce transaction costs, offering enterprises more stable profit expectations and enhancing financial security for their digital transformation initiatives [18]. This leads us to the statement of Hypothesis 2:

H2: *The marketization of data elements promotes improvements in the digital transformation level of manufacturing enterprises by reducing costs.*

For manufacturing enterprises, significant investment costs and financing constraints represent critical challenges in progressing toward digital transformation [19]. Because of the opacity of information in the capital market, the risk-averse nature of financial institutions, and the misallocation of capital resources, enterprises in China generally face more severe financing constraints [20]. The advancement of the marketization of data elements offers a novel solution to mitigate this dilemma. By enhancing the transparency of enterprise operations, the marketization of data elements enables investors and financial institutions to more accurately evaluate the value and risks associated with enterprises. This process effectively reduces the barriers to financing caused by information asymmetry, thereby lowering both the cost and difficulty of securing funding [21]. Furthermore, when companies successfully alleviate their financing constraints through the marketization of data elements, they can allocate greater resources and attention to corporate innovation and management transformation. This, in turn, fosters a virtuous cycle. At the same time, the deeper development of the data element market can also help financial institutions accelerate their digital upgrades by leveraging digital technologies to accurately identify the funding needs and potential risks of manufacturing enterprises during their digital transformation process. For example, JPMorgan Chase in the United States uses a data-driven risk assessment system to design differentiated financial support plans for enterprises. This data-driven service capability provides strong financial backing for the digital transformation of manufacturing enterprises [22]. This leads us to the statement of Hypothesis 3:

H3: *The marketization of data elements enhances the digital transformation of manufacturing companies by reducing financing constraints.*

The marketization of data elements plays a critical role in optimizing and innovating the digital economy ecosystem by connecting various elements, strengthening collaboration, and promoting development. It provides comprehensive foundational support for the integration and innovation of digital technologies. By enhancing data exchange and cooperation across different industries and sectors within a region, enterprises and research institutions can establish collaborative networks to jointly develop data-driven innovative technologies, thereby contributing to the increase in the region's technological intensity [23]. Digital technology serves as a crucial foundation for the digital transformation of enter-

prises. The digital transformation process of enterprises involves the development and implementation of digital technologies within their production and operational frameworks [24]. The widespread application of digital technologies enables enterprises to gain profound market insights through advanced data analytics, facilitating more effective marketing and personalized customer services. For example, the state-owned China National Energy Investment Group has integrated data from various transportation equipment, including operational, failure, and maintenance data, and codeveloped over 20 specialized data analysis tools and models. These tools are used to analyze the efficiency and reliability of transportation equipment, offering users solutions for collaborative manufacturing and the optimization of transportation assets [25]. The integration and innovation of digital technologies are driving unprecedented transformations in enterprises, injecting vitality into their sustained growth and competitive advantage. Furthermore, the marketization of data elements is often accompanied by improvements in urban digital infrastructure, such as high-speed internet and data centers. These infrastructures provide reliable support for the implementation of digital technologies, enhancing the efficiency and quality of professional services. This leads us to the statement of Hypothesis 4:

H4: *The marketization of data elements accelerates the digital transformation of manufacturing enterprises by enhancing the level of regional digital technology innovation.*

Digital transformation encompasses more than merely upgrading technology; it involves profound alterations in business models and the methodologies through which value is generated [26]. Manufacturing companies must investigate innovative business models, including service-oriented manufacturing and personalized customization, to effectively address the demands of the digital economy era [27]. This innovation process requires substantial digital talent, such as data analysts and software developers [28]. People with relevant expertise are essential for the implementation, maintenance, and optimization of digital technologies. The advancement of the marketization of data elements has enhanced the appeal and competitiveness of cities in the realm of digital services. This development has facilitated the agglomeration of enterprises and talent, leading to the formation of dynamic clusters within the digital service sector. For instance, the Panyu Artificial Intelligence and Digital Economy Pilot Zone in Guangzhou, China, has taken the lead in nationwide data element market reforms, bringing together over 3000 enterprises in data-related fields. It has empowered more than 850,000 businesses and driven nearly CNY 50 billion in economic benefits [29]. The dense digital service industry provides specialized consulting services for the digital transformation of manufacturing enterprises, helping them assess their current status, plan transformation paths, and develop feasible digital strategies tailored to the specific needs and characteristics of each enterprise. The digital culture and innovation environment fostered by the concentration of digital services also help enterprises build a shared understanding of digital transformation, promoting changes in organizational culture and work practices. This leads us to the statement of Hypothesis 5:

H5: *The marketization of data elements enhances the digital transformation of manufacturing enterprises by enhancing the clustering effect of the digital service industry.*

3. Research Design

3.1. Empirical Model Design

Since 2014, the development of data trading platforms has undergone nearly a decade-long "long march". According to data published at the 2023 China International Big Data Industry Expo, the annual scale of data exchange transactions in China reached

approximately CNY 4 billion in 2022 [30]. The construction of data trading platforms varies across cities and time periods. Therefore, employing a multiperiod asymptotic difference-in-differences (DID) approach for empirical testing can effectively control for changes in outcome variables induced by extraneous factors. This methodology allows for an accurate assessment of the net impact that the establishment of data trading platforms has on the digital transformation of manufacturing enterprises. Drawing on the work of Liu et al. (2022) and Bertrand et al. (2004) [31,32], the establishment of a government-led data trading platform was conceptualized as a quasinatural experiment in the marketization of data elements. In this context, cities that establish such platforms are classified as the treatment group, while those that do not serve as the control group. The specific model is structured as follows:

$$\text{digital}_{\text{cyn}} = \alpha_0 + \alpha_1 \text{did}_{cy} + \alpha_2 X_{\text{cyn}} + \delta_{\text{n}} + \delta_{\text{y}} + \varepsilon_{\text{cyn}} \quad (1)$$

where subscript c denotes the city, y denotes the year, and n denotes the firm. The dependent variable $\text{digital}_{\text{cyn}}$ denotes the degree of the digital transformation of firms, indicating the level of digital transformation of firm n that occurred in city c in year y. Explanatory variables did_{cy} are dummy variables for whether a data trading platform is established. Based on Hypothesis 1 of this paper, it was expected that the coefficient value α_1 of did_{cy} would be positive, indicating that the construction of the marketization of data elements positively affects the digital transformation of manufacturing firms. X_{cyn} is a control variable; δ_{n} and δ_{y} denote the firm fixed effects and year fixed effects, respectively; and $\alpha 2$ is the coefficient of the control variable X_{cyn}, indicating the impact of the control variable X_{cyn} on the explained variable $\text{digital}_{\text{cyn}}$. ε_{cyn} is a randomized disturbance term.

3.2. Variable Selection

The degree of the digital transformation of enterprises (digital) was measured by using the frequency counts of characteristic words involving "digital transformation" in the annual reports of listed manufacturing enterprises, drawing on the studies of Wu et al. (2021), Ren et al. (2023), and Li et al. (2023) [33–35]. In this study, we used the frequency counts of feature words related to "digital transformation" in the annual reports of listed manufacturing companies to measure the degree of digital transformation. The "China Digital Economy Research Database" in the CSMAR database adopts the practice of Wu Fei et al. (2021) [33] to form a comprehensive measure of enterprise digital transformation. This study applied the natural logarithm of this comprehensive measure as a proxy variable for enterprise digital transformation.

The marketization of data elements (did): From the actual operation of the marketization of data elements, some scholars tend to equate data trading platforms, data exchanges, and other practice spaces with data element markets. The establishment of data trading platforms is indeed an important symbol of the marketization of data elements, providing a place and mechanism for data trading and promoting the circulation and value realization of data [36]. In reference to existing research, the year in which the first government-led data trading platform was established in each city was used as the starting year for the marketization of data elements in that city [31]. If the city established a data trading platform in that year, the value of did was assigned to 1; otherwise, it was assigned to 0.

Control variables: Differences in firm age, top management, and profitability lead to different risk preferences and resource allocation in digital transformation, significantly impacting manufacturing firms' digital transformation outcomes [37,38]. Regional disparities in development levels, industrial composition, and infrastructure lead to variations in digital talent availability, technological proficiency, and digital policy frameworks. These factors also exert a multifaceted and dynamic influence on the digital transformation pro-

cesses of manufacturing enterprises [39,40]. Referring to the studies of Han and Yang (2024), Soedaryono and Riduifana (2013), Pelcher (2019), and Capello and Lenzi (2019) [41–44], this study selected control variables at both the enterprise and city levels to account for the potential interference of enterprise-specific and regional differences with respect to the research results. The control variables at the firm level were selected as follows: firm age (FirmA), board size (BoardS), average age of management (ManAge), fixed asset ratio (FixAsset), income tax rate (Tax), and earnings volatility (EarningsV). The control variables at the city level were selected as follows: regional gross domestic product per capita growth rate (RGDP), regional natural population growth rate (PopGrow), regional urbanization rate (Urban), and regional industrial structure (IndusStruc).

This section introduces the selection of research variables. For more detailed explanation of variable construction, see Appendix A.

3.3. Data Sources and Descriptive Statistics

The research sample consisted of China's A-share listed manufacturing companies on the Shanghai Stock Exchange and the Shenzhen Stock Exchange from 2013 to 2022. The data for the listed manufacturing companies were obtained mainly from the CSMAR database, the China Research Data Service Platform (CNRDS), and corporate annual reports. Urban macroeconomic indicators were obtained from the China Urban Statistical Yearbook and provincial statistical yearbooks. Data on the time of establishment of data trading platforms were obtained from announcements and news statistics compiled by a total of 48 data trading platforms. The data sources and acquisition addresses are shown in Appendix B. The raw data were processed as follows to avoid the impact of abnormal data: 1. samples of companies labeled as ST and *ST in the current year were excluded; 2. samples of companies that had been delisted were excluded; 3. samples of companies with serious missing data were excluded. All variables were preprocessed with a 1% shrinking tail to improve the accuracy of estimations. A total of 17,676 observations were obtained, and Table 1 demonstrates the descriptive statistics of the main variables.

Table 1. Descriptive statistics of relevant variables.

Variable	N	Min	Mean	Max	Std
digital	17,676	0	1.389	5.024	1.280
did	17,676	0	0.322	1	0.467
FirmA	17,676	1.609	2.872	3.583	0.324
BoardS	17,676	1.609	2.099	2.708	0.180
ManAge	17,676	3.727	3.898	4.048	0.064
FixAsset	17,676	0.0099	0.212	0.663	0.129
Tax	17,676	−1.009	0.131	1.692	0.174
EarningsV	17,676	0.001	0.035	0.378	0.044
RGDP	17,676	−10.93	6.820	298.84	10.532
PopGrow	17,676	−6.390	2.768	25.18	5.348
Urban	17,676	0.315	0.758	1.007	0.145
IndusStruc	17,676	0	2.304	2.836	0.706

4. Empirical Test Results and Analysis

4.1. Baseline Regression

Table 2 reports the results of the baseline regression on the impact of the marketization of data elements on the digital transformation of manufacturing firms. Column (1) contains only the core explanatory variables, to which column (2) adds corporate governance-related control variables, while column (3) further controls for urban macroeconomic indicators. In the three sets of regression results, the coefficients for the explanatory

variable—the marketization of data elements (did)—were 0.123, 0.124, and 0.122, and all were significantly positive at the 1% level. Therefore, the results supported Hypothesis H1, indicating that the marketization of data elements can enhance the digital transformation level of manufacturing enterprises.

Table 2. Baseline regression results for the marketization of data elements and the digital transformation of manufacturing enterprises.

	(1)	(2)	(3)
VARIABLES	**Digital**	**Digital**	**Digital**
did	0.123 ***	0.124 ***	0.122 ***
	(0.0314)	(0.0313)	(0.0313)
FirmA		0.100	0.0886
		(0.177)	(0.177)
BoardS		0.209 ***	0.204 ***
		(0.0788)	(0.0791)
ManAge		−0.105	−0.117
		(0.261)	(0.260)
FixAsset		−0.361 ***	−0.367 ***
		(0.119)	(0.119)
Tax		−0.0160	−0.0159
		(0.0330)	(0.0329)
EarningsV		−0.264	−0.273
		(0.194)	(0.194)
RGDP			5.33×10^{-5}
			(0.000605)
PopGrow			−0.00269
			(0.00197)
Urban			−0.248
			(0.240)
IndusStruc			0.00208
			(0.0163)
Constant	1.349 ***	1.120	1.402
	(0.0101)	(1.108)	(1.126)
Observations	17,676	17,676	17,676
Firm Fixed Effect	YES	YES	YES
Year Fixed Effect	YES	YES	YES
R-Squared	0.793	0.793	0.793

Note: *** indicates significance at the 1% statistical levels; standard errors are in parentheses.

4.2. Parallel Trend Test

When using the progressive difference-in-differences (DID) approach, it is required that the treatment group (i.e., the group that is subject to the intervention) and the control group (i.e., the group that is not subject to the intervention) are parallel in terms of the trend in the development of the outcome variable before the intervention policy or treatment effect is implemented. Since the timing of the marketization of data elements varies across cities, it was not possible to adopt a single point in time as a uniform criterion for policy implementation. Therefore, a dummy variable for the relative timing of the marketization of data elements was set for each city in order to accurately capture the temporal dynamics before and after policy implementation. The following model was constructed for parallel trend testing:

$$\text{digital}_{\text{cyn}} = \beta_0 + \beta_1 \text{D}_{\text{cy}}^{\text{q}} + \beta_2 \text{X}_{\text{cyn}} + \delta_{\text{n}} + \delta_{\text{y}} + \varepsilon_{\text{cyn}} \quad (2)$$

where the time dummy variables are observations in the q years before, in the current year, and in the q years after the establishment of the first data trading platform in each city, and

the rest of the variables have the same meaning as in model (1). A parallel trend test was carried out with the first period, i.e., period −10, as the base period; Figure 3 reports the results. The solid points represent the data, and the dashed lines indicate the 99% confidence interval. The test results showed that the estimated coefficients of the marketization of data elements variable were not significant from the -9th to the -2nd period, indicating that, in the absence of policy intervention, the digital transformation trends of manufacturing enterprises in both the treatment and control groups were consistent, thereby supporting the assumption of parallel trends. The results indicated that the estimated coefficient in period −1 was statistically significant. This significance may be attributed to the release of relevant approval announcements prior to the official establishment of the data trading platform, which likely influenced enterprise decision-making. Subsequently, coefficient β_1 became significantly positive, and the overall trend exhibited an upward trajectory, indicating that the establishment of data trading platforms significantly enhanced the digital transformation of enterprises. Further analysis reveals that this impact initially increased and then decreased, and later, it increased again. This may be due to the fact that, in the early stages of the marketization of data elements, enterprises acquired high-quality data resources through data trading platforms, significantly reducing data acquisition costs and improving the efficiency of digital transformation in manufacturing enterprises. Over time, however, the technical challenges faced by enterprises, such as data security issues, may have led to hesitation and a wait-and-see attitude, weakening the promotional effect of the marketization of data elements on digital transformation. After a period of adjustment and adaptation, enterprises gradually overcame the technical integration challenges faced in the early stages, and the facilitative effect strengthened once more.

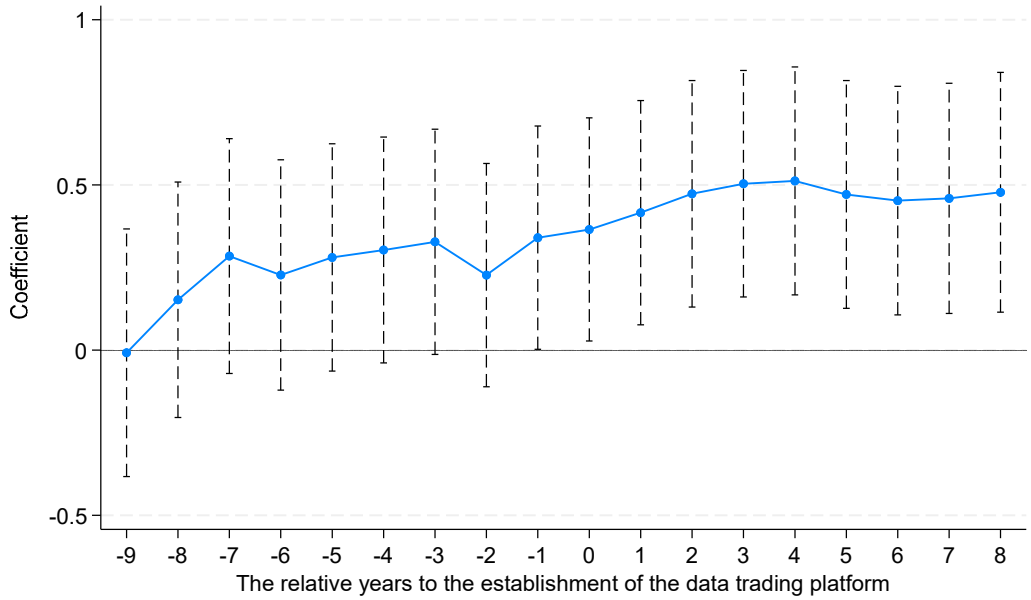


Figure 3. Parallel trend test. The dashed lines represent 99% confidence intervals.

4.3. Robustness Tests

4.3.1. Robustness Test Based on Model Settings

A multitemporal double-difference propensity score matching model (PSM-DID) was adopted to address potential selectivity bias due to differences in sample characteristics. The method centers on finding individuals who are similar in key characteristics between the treatment and control groups by selecting a series of covariates to ensure comparability between the two sample groups. During the matching process, based on these covariates, one or more samples that are similar in the control group are found for each treatment

group sample to construct a balanced dataset, and unsuccessful matches are excluded. Three methods, nearest neighbor matching, radius matching, and kernel matching, were used, each based on the original set of control variables. Three new datasets were generated using each of the three matching methods, and these matched datasets were subsequently employed for regression analyses. Table 3 presents the regression results obtained from these three matching techniques. The coefficients of the explanatory variables, shown in columns (1) to (3), were 0.157, 0.122, and 0.122, respectively, all of which were significantly positive at the 1% level. This indicates that the positive impact of the marketization of data elements on the digital transformation of enterprises is genuine and not due to sample differences, thereby confirming the robustness of the baseline regression results.

Table 3. Regression results after propensity score matching.

	(1)	(2)	(3)
VARIABLES	**Digital**	**Digital**	**Digital**
	nearest neighbor matching	radius matching	kernel matching
did	0.157 ***	0.122 ***	0.122 ***
	(0.0466)	(0.0313)	(0.0313)
Constant	2.289	1.402	1.402
	(1.398)	(1.126)	(1.126)
Observations	12,080	17,676	17,676
Firm Fixed Effect	YES	YES	YES
Year Fixed Effect	YES	YES	YES
R-Squared	0.776	0.793	0.793

Note: *** indicates significance at the 1% statistical levels; standard errors are in parentheses.

4.3.2. Placebo Test

Despite the incorporation of numerous control variables in quasinatural experimental designs, there remains a risk of bias stemming from the omission of certain variables. To ensure that the findings of this study were attributable to data trading platforms rather than random factors, we adopted the research methodology established by Chetty et al. (2009) [45]. This involved generating virtual policy pilot cities through random sampling and applying them within our benchmark regression model. The kernel density distribution of the estimated coefficients of the explanatory variables was obtained after 500 repetitions of the simulation (Figure 4). These regression coefficients roughly followed a normal distribution with a mean of 0, and none of the estimated coefficients obtained exceeded the threshold of 0.122 for the actual regression coefficient. This finding suggests that even in the presence of unobserved influences, their impact on the study's conclusions would be minimal, thus validating the robustness of the study's core findings.

4.3.3. Exclusion of Other Policy Effects

To ensure the accuracy of the study's results, the analysis of the impact of the marketization of data elements on enterprises' digital transformation specifically accounted for and controlled other relevant policies implemented during the same period. Specifically, the "Broadband China" policy may have indirectly contributed to the digitization of enterprises through the enhancement of Internet infrastructure. Public data openness policies, on the other hand, provide direct support for enterprise digital transformation by expanding data resources. Given the possible overlap between these two policies and the marketization of data elements in terms of objectives and impact mechanisms, the potential interference of these policies was controlled for by the inclusion of a dummy variable for the "Broadband China" policy (did2) and a dummy variable for the public data openness policy (did3) in the regression model (1). The results in columns (1) to (3) of Table 4 show that after controlling

for the effects of the open public data policy and the Broadband China policy separately, as well as simultaneously controlling for the effects of both policies, the coefficients of the core explanatory variable, did, were 0.119, 0.123, and 0.121, respectively. The direction and significance of the coefficients remained consistent with the baseline regression, indicating that the positive impact of the marketization of data elements on the digital transformation of enterprises remains robust. This confirms the central role of the marketization of data elements in driving the digital transformation of enterprises.

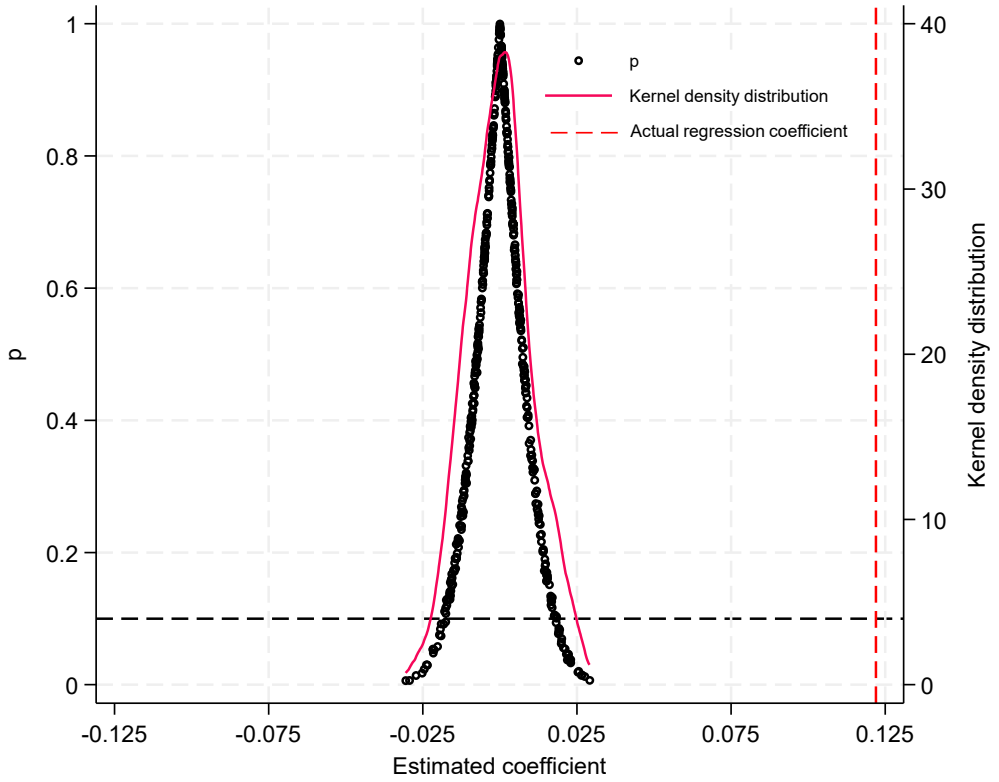


Figure 4. Placebo test.

Table 4. Excluding other policies and sample data to screen the robustness test regression results.

	(1)	(2)	(3)	(4)
VARIABLES	**Digital**	**Digital**	**Digital**	**Digital**
did	0.119 ***	0.123 ***	0.121 ***	0.192 ***
	(0.0313)	(0.0313)	(0.0314)	(0.0543)
did2		−0.0268	−0.0253	
		(0.0381)	(0.0381)	
did3	0.0452 *		0.0448 *	
	(0.0271)		(0.0271)	
Constant	1.419	1.419	1.435	3.277 **
	(1.127)	(1.127)	(1.128)	(1.520)
Control Variables	YES	YES	YES	YES
Observations	17,676	17,676	17,676	10,404
Firm Fixed Effect	YES	YES	YES	YES
Yesar Fixed Effect	YES	YES	YES	YES
R-quared	0.793	0.793	0.793	0.782

Note: ***, ** and * indicate significance at the 1%, 5%, and 10% statistical levels, respectively; standard errors are in parentheses.

4.3.4. Sample Data Screening

Since provincial capital cities and municipalities typically serve as the epicenters of regional development, there exist notable disparities in economic development levels, in-

dustrial structures, and innovation capacities when compared with other cities. To mitigate the potential influence of these disparities on the study's outcomes, samples from provincial capital cities and municipalities—such as Beijing, Shanghai, and Guangzhou—were excluded to prevent extreme values from skewing the results. The regression results in column (4) of Table 4 indicate that the coefficient of the core explanatory variable, did, remained significantly positive at the 1% level, with a value of 0.192. This suggests that after excluding the relevant samples, the primary conclusion remained substantively unchanged, demonstrating the robustness of the findings. One plausible explanation for the change in the coefficients is that firms in provincial capitals and municipalities likely possessed stronger pre-existing digital resources and capabilities before the establishment of data trading platforms, thereby diminishing the marginal impact of data marketization. In contrast, manufacturing enterprises in second-tier and lower-tier cities may have had greater potential for digitalization. With access to structured data trading platforms, these firms likely experienced a stronger transformational push, leading to a more pronounced estimated impact. Consequently, after excluding certain city samples, the regression coefficient exhibited a significant increase.

4.4. Further Study

4.4.1. Mechanism Checking

Although the facilitating effect of the marketization of data elements on the digital transformation of manufacturing enterprises was confirmed in the previous section, its pathway of action was not tested. Drawing on the research of Jiang (2022) [46], the following model was constructed to test the mechanism of action using a two-step approach.

$$\mathrm{Mid}_{cyn} = \gamma_0 + \gamma_1 \mathrm{did}_{cy} + \gamma_2 \mathrm{X}_{cyn} + \delta_n + \delta_y + \varepsilon_{cyn} \quad (3)$$

Mid_{cyn} denotes the mechanism variable, and the other variables in model (3) have the same meaning as in model (1).

Business costs: Referring to the studies of Han and Yang (2024) [41] and Wu et al. (2015) [47], the management expense ratio (ManExpenceR) and the proportion of selling expenses to the main business income (SelExpenseR) were used to represent the cost of the enterprise. As shown in columns (1) and (2) of Table 5, the regression coefficients were −0.00518 and −0.00156, respectively, indicating that the marketization of data elements has a significant negative impact on both enterprise management and sales costs. Specifically, with the advancement of the market-oriented reform of data elements, the costs of enterprises in data acquisition, processing, and analysis have been effectively reduced. First, the market-oriented reform of data elements enhances the efficiency of data resource utilization by optimizing their allocation. This allows enterprises to acquire high-quality data resources at a more economical cost. Second, the establishment of data trading platforms offers standardized and regulated services for data transactions, thereby reducing the time and effort expended by enterprises in these processes. Additionally, the marketization of data elements may lower operational costs for enterprises by improving internal management efficiency. These cost savings free up additional capital for businesses, enabling them to invest in research, development, and application of digital technologies, thus accelerating their digital transformation efforts. Therefore, the data results supported Hypothesis H2, which states that the marketization of data elements facilitates the digital transformation of manufacturing firms through cost reduction.

Financing constraints (FC): Higher values of the FC index indicate that firms are experiencing more stringent financing constraints. As shown in column (3) of Table 5, the regression coefficient for the FC index was −0.0124, indicating that the marketization of data elements has a significant negative impact on the level of financing constraints faced

by enterprises. This finding suggests that the marketization of data elements has played an important role in alleviating the financing constraints of enterprises. By providing more transparent data information, the marketization of data elements has enhanced financial institutions' understanding of the creditworthiness of enterprises, thereby reducing the cost and difficulty of enterprise financing. In addition, the marketization of data elements may also provide companies with more financing options adapted to their digital transformation needs by fostering innovation in financial products and services. These reform initiatives effectively alleviate the financing constraints of enterprises and provide a more relaxed financial environment for their digital transformation. The data results supported Hypothesis H3, which states that the marketization of data elements promotes the digital transformation of manufacturing enterprises by reducing financing constraints.

Table 5. Mechanism test regression results.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	**ManExpenceR**	**SelExpenseR**	**FC**	**Dtech**	**Dsa**
did	−0.00518 ***	−0.00156 ***	−0.0124 *	0.0670 ***	0.0826 ***
	(0.00173)	(0.000592)	(0.00635)	(0.0219)	(0.0208)
Constant	0.282 ***	0.144 ***	2.485 ***	6.713 ***	−0.438
	(0.0771)	(0.0255)	(0.260)	(0.671)	(0.672)
Control Variables	YES	YES	YES	YES	YES
Observations	17,674	17,676	17,122	17,666	17,430
Firm Fixed Effect	YES	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES	YES
R-squared	0.734	0.750	0.813	0.984	0.923

Note: *** and * indicate significance at the 1%, and 10% statistical levels, respectively; standard errors are in parentheses.

Digital technology innovation (Dtech): Referring to Sun et al.'s (2022) study [48], the logarithm of the number of digital economy patent applications plus one in a city measures the city's level of digital technology innovation (Dtech) for the year. As shown in column (4) of Table 5, the regression coefficient for Dtech was 0.067, indicating a significant positive correlation between the marketization of data elements and the level of digital technology innovation. This finding confirms the positive role of the marketization of data elements in enhancing regional digital technology innovation. By promoting the effective circulation and sharing of data resources, the marketization of data elements has provided rich data support for technological innovation and accelerated the pace of technological innovation. At the same time, the marketization of data elements has the potential to create a robust innovation ecosystem by attracting a greater number of high-tech enterprises and innovative talents. This, in turn, can significantly enhance the region's capacity for technological innovation. Digital technology innovation accelerates the digitization of industries through advancements in product and service offerings, as well as improvements in operational efficiency [49]. Consequently, the data findings supported Hypothesis H4, which posits that the development of a market for data elements facilitates the digital transformation of manufacturing enterprises by enhancing regional levels of digital technology innovation.

Clustering of digital services (Dsa): Referring to the study of Zhao et al. (2024) [50], the location entropy index of the number of employees in the information transmission, software, and information technology service industry was used as a proxy variable for digital service agglomeration (Dsa). As shown in column (5) of Table 5, the regression coefficient for Dsa was 0.0826, indicating a significant positive correlation between the marketization of data elements and the agglomeration of the digital service industry. This finding suggests that the marketization of data elements plays an important role in enhancing the clustering effect of digital services. By facilitating the concentration

of digital service resources, the market-oriented reform of data elements has endowed enterprises with more abundant and efficient digital services. These services encompass cloud computing, big data analytics, and artificial intelligence applications, which have collectively contributed to enhancing productivity, optimizing business processes, and fostering innovation in business models. At the same time, the clustering of the digital services industry has also brought about the spillover effect of knowledge and technology and promoted collaborative innovation among enterprises. These factors work together to enhance the digital transformation of manufacturing enterprises. Therefore, the data results supported Hypothesis H5, which states that the marketization of data elements facilitates the digital transformation of manufacturing firms by enhancing the clustering effect of digital services.

4.4.2. Heterogeneity Analysis

There are notable differences in resource endowments and advantages concerning the development of digital industries across various regions, which may lead to divergent impacts of the marketization of data elements on the digital transformation of enterprises. Cities were categorized into distinct groups based on their geographical locations and analyzed separately. Table 6 presents the regression results for the eastern, central, and western region groups in columns (1), (2), and (3), respectively. The regression coefficients were 0.105, −0.00551, and 0.291, respectively. The findings indicate that the marketization of data elements (did) exerts a significant positive effect on the digital transformation (digital) of firms in both the eastern and western regions; however, this impact is not statistically significant for the central region. This phenomenon may be attributed to the fact that the eastern region possesses a more developed market economic environment, a higher level of informatization, and a greater capacity for innovation. Consequently, enterprises in this area tend to be more receptive to new technologies and demonstrate an enhanced ability to implement them effectively. Furthermore, the establishment of a data element market is likely to have a more significant impact in these regions. The western region, driven by specific market demands and policy orientations, has exhibited a proactive approach toward digital transformation. It has actively sought human resources and technological assets conducive to the digital transformation of enterprises through the marketization of data elements. In contrast, the central region may encounter challenges in attracting and retaining talent and technological resources. With a relatively less competitive market environment and diminished pressure, enterprises in this area may not experience the same level of urgency or demand for digital transformation as their counterparts in the eastern region. This situation consequently limits the effectiveness of the marketization of data elements in facilitating digital transformation efforts.

Separate regressions were run based on property right heterogeneity, and the results are reported in columns (4) and (5) of Table 6. The regression coefficients for the state-owned and non-state-owned enterprise groups were 0.153 and 0.101, respectively. The results indicate that the marketization of data elements has a positive impact on the digital transformation of state-owned enterprises (SOEs) and non-state-owned enterprises (NSOEs) at the 5% and 1% significance levels, respectively. This finding may indicate that both SOEs and NSOEs are capable of effectively leveraging data resources to propel their digitalization efforts, a process facilitated by a market-oriented approach to data elements. Although the regression coefficients for state-owned enterprises were larger than those for non-state-owned enterprises, both groups exhibited significantly positive coefficients for the explanatory variables in their regression results. Therefore, a Fisher test was employed to assess whether the differences between the coefficients of these two groups are statistically significant. The results indicated a significant difference between

the two groups of coefficients at the 10% statistical level, suggesting that the marketization of data elements exerts a more pronounced influence on the digital transformation of state-owned manufacturing enterprises. This phenomenon may be attributed to the fact that state-owned enterprises typically possess stronger resource integration capabilities and greater responsiveness to policy changes. Consequently, they are better positioned to effectively leverage resources such as data, talent, and technology provided by the data element market to facilitate their digital transformation processes.

Table 6. Heterogeneity test of regression results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	**Digital**	**Digital**	**Digital**	**Digital**	**Digital**	**Digital**	**Digital**
	East	Middle	West	SOEs	NSOEs	Overseas experience	No overseas experience
did	0.105 ***	−0.00551	0.291 ***	0.153 **	0.101 ***	0.0558	0.157 ***
	(0.0372)	(0.0678)	(0.0984)	(0.0615)	(0.0363)	(0.0400)	(0.0522)
Constant	0.785	−1.496	3.684	2.479	0.574	−0.747	2.239
	(1.301)	(2.788)	(3.185)	(2.391)	(1.284)	(1.374)	(1.878)
Control Variables	YES	YES	YES	YES	YES	YES	YES
Observations	12,676	2935	2065	4542	13,134	10,549	7127
Firm Fixed Effect	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES	YES	YES	YES
R-Squared	0.240	0.255	0.249	0.261	0.227	0.233	0.210

Note: *** and ** indicate significance at the 1% and 5% statistical levels, respectively; standard errors are in parentheses.

The overseas experience of corporate executives significantly influences corporate behavior. The sample firms were categorized into two groups: executives with overseas backgrounds and those without these backgrounds. Separate regressions were conducted for each group, and the regression results are presented in Table 6, columns (6) and (7). The regression coefficients were 0.0558 and 0.157, respectively. Executives with overseas experience do not contribute significantly to the digital transformation of their companies, and companies with executives who do not have overseas experience perform better in digital transformation. This finding may initially appear counterintuitive. While the overseas experience of executives does, in certain instances, facilitate companies in acquiring and implementing advanced international digital technologies and management practices, this positive impact may be mitigated by other factors. Alternatively, these experiences might not have directly contributed to the process of digital transformation. Executives lacking overseas experience may possess a more profound understanding of the local market and exhibit a greater capacity for adaptation, which can positively influence digital transformation efforts. They are likely to prioritize the localization of their resources and strategies, potentially yielding more effective outcomes in specific market contexts. This observation offers new insights for further research, suggesting that local experience and an in-depth comprehension of the local market may be equally critical in the process of digital transformation.

5. Conclusions

5.1. Summary and Conclusions

Based on data from 2013 to 2022, this study delves into how the marketization of data elements facilitates the digital transformation process of manufacturing companies and draws the following conclusions. First, the marketization of data elements exerts a positive influence on the digital transformation of manufacturing firms and serves as a significant source of dynamics driving their digital transformation. This conclusion is

consistent with the view of Sestino et al. [51], who pointed out that the data economy and the data element market are key drivers of digital transformation in enterprises. This study further validated this through empirical analysis, particularly in the context of China's manufacturing industry, providing empirical evidence on the specific impact of the marketization of data elements on digital transformation. This conclusion remained robust even after conducting various tests, including parallel trend analysis, propensity score matching, placebo testing, the exclusion of other policy interferences, and sample data screening. Second, the marketization of data elements facilitates the digital transformation of enterprises primarily indirectly through several mechanisms: the cost-saving effect, the financing constraint effect, the innovation effect of digital technologies, and the agglomeration effect within the digital service industry. This study reveals the multidimensional impact of the marketization of data elements on the transformation of manufacturing enterprises. The financing constraint effect not only supports the viewpoint of Xu et al., who argued that lower financing constraints promote digital transformation in enterprises, but contributes to existing research on how the marketization of data elements influences financing constraints [19]. Third, the development of a market for data elements had a positive impact on the digital transformation of manufacturing enterprises in both eastern and western regions; however, this effect was not significantly observed in the central region. The construction of a data element market can facilitate digital transformation for both state-owned and non-state-owned enterprises. State-owned enterprises may exhibit a stronger motivation for digital transformation due to their enhanced capacity to integrate resources and respond effectively to policies. Conversely, executives without overseas experience tend to leverage the data element market more effectively to promote their digital transformation compared to those with international experience, owing to their deeper understanding of and adaptability to the local market.

5.2. Policy Recommendations

We recommend optimizing the functions of the data trading platform and accelerating the process of the marketization of data elements. In light of the pivotal role that data trading platforms play in advancing intelligent manufacturing, it is recommended that government entities and relevant departments take further steps to optimize the functionalities of these platforms. Enhancing the transparency and efficiency of data trading processes is crucial, as is strengthening the foundational support that data trading platforms provide for enterprise digital transformation. Specifically, by optimizing data transaction regulations, improving data quality supervision, and offering specialized consulting and support services, we can reduce the uncertainties and risks enterprises face during data transactions. This approach not only lowers transaction costs but improves decision-making efficiency. Simultaneously, it is important to implement advanced data encryption and privacy protection measures in the data trading market to ensure data security, build enterprise trust, promote data sharing, and address financing challenges caused by information asymmetry. Furthermore, the government should enhance platform support to improve data sharing and establish an open cooperation mechanism. This will help resolve data isolation issues and promote interoperability across industries. While ensuring robust data security and privacy protection, it is crucial to incentivize collaboration among enterprises in order to provide richer innovation resources for manufacturing enterprises. Data trading platforms, financial institutions, scientific research organizations, and other relevant entities should be guided and supported in their collaboration to establish an ecosystem for the marketization of data elements. This initiative aims to leverage the strengths of all involved parties and comprehensively support the digital transformation of manufacturing enterprises.

We also recommend reliance on data trading platforms to strengthen digital technology and talent support, which will help enhance the digitalization capabilities of enterprises. This is because the marketization of data elements facilitates the digital transformation of enterprises by fostering innovation in digital technologies and promoting the clustering of digital service industries. It is recommended that the government leverage data trading platforms to enhance the research, development, and application of digital technologies. A mechanism should be established for talent training and recruitment through these platforms, particularly in critical technological domains such as data analysis, cloud computing, and artificial intelligence. Then, the attractiveness of the market-based construction of data elements relative to technology and talents can be grasped, and they can be transformed into intrinsic motivations for the digital transformation of enterprises. On the one hand, the government should strengthen the construction of digital infrastructure to provide a solid foundation for digital technology innovation and service industry agglomeration. Moreover, the construction of key network infrastructure such as 5G and edge computing should be promoted, especially in manufacturing-intensive industrial parks, to realize high-speed and low-latency data transmission. The development of edge computing centers should be encouraged to enhance the real-time and localized capabilities of data processing in order to support real-time analysis and the application of complex data. On the other hand, the government can optimize the business environment by simplifying administrative procedures and providing one-stop services to attract more digital technology enterprises and talents to settle in the country. By streamlining the processes of business registration and project approval and providing online one-stop services for enterprises, the government can reduce administrative barriers for enterprises to move in. Moreover, it can provide policy incentives such as tax breaks and R&D subsidies to enterprises engaged in the research and development of digital technologies such as big data, artificial intelligence, and cloud computing. Through the above measures, the government can maintain digital technology innovation and industrial agglomeration advantages brought about by the data element market and provide sustained external support for the digital transformation of manufacturing enterprises.

Formulating differentiated digital transformation support policies based on regional advantages and enterprise characteristics is crucial. The marketization of data elements has had a significant positive impact on the digital transformation of manufacturing enterprises in both the eastern and western regions, while its effects in the central region remain less pronounced. Therefore, policymakers should develop differentiated support policies tailored to the varying levels of regional economic development and industrial characteristics. For the eastern and western regions, policies should focus on further optimizing the environment for the marketization of data elements and promoting the efficient allocation of data resources. As the leading area of the development of China's digital economy, the eastern region should continue to strengthen the application and innovation of digital technologies through the data element market, driving the digital transformation of industries to a new level. Specifically, regional-level digital technology innovation funds can be established to support the research and development of advanced digital technologies, such as artificial intelligence, big data, and the Internet of Things, which are all based on high-quality data. In addition, enterprises should be encouraged to establish industry–academia–research cooperation with universities and research institutions to expedite the transformation of technological achievements into productive forces. The western region can fully leverage its advantages, such as abundant land, green electricity resources, and lower temperatures, to develop data and computing power centers. By accelerating the construction of digital infrastructure, the region can facilitate the trading and circulation of data products, enhance the real-time processing

of data, and improve application efficiency, thereby providing the foundational support necessary for manufacturing enterprises to achieve efficient digital transformation. For the central region, it is crucial to enhance the efficiency with which enterprises utilize data elements. Through market mechanisms and policy guidance, competition pressures should be increased to stimulate enterprises' motivation for digital transformation. Support should be directed toward industry leaders, encouraging the coconstruction of scenario-driven, technology-compatible, and standard-interoperable industry-specific trusted data spaces with upstream and downstream enterprises. This will promote the innovative use of data resources and drive digital collaborative innovation across the entire industry chain. Simultaneously, policies should consider the distinct characteristics of different types of enterprises and provide tailored support for both state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs). This includes offering directional guidance and process optimization for SOEs, as well as tax incentives and digital training for non-SOEs. This dual approach aims to fully leverage the integration and responsiveness of SOEs while enhancing the flexibility and adaptability of non-SOEs. Enterprises led by executives with limited overseas experience but profound knowledge of the local market should be prioritized. Such enterprises should receive increased resource support and a stronger voice to help cultivate local talent that can drive the digital transformation of their organizations.

5.3. Limitations and Further Research

Although this study investigated the facilitating effect of the marketization of data elements on the digital transformation of manufacturing firms through a multiperiod difference-in-differences (DID) model and identified mechanisms such as cost reduction, the alleviation of financing constraints, and the promotion of technological innovation, it also acknowledges certain limitations and areas for further improvement. First, the time span of the research sample was 2013–2022, which covered the key stages of the development of the marketization of data elements, but it was therefore difficult to observe the long-term, far-reaching impact of this development. Second, for the mining of mechanisms, although several important paths were analyzed, the analysis failed to encompass potential mechanisms such as the cross-industry sharing of data and policy incentives, which may have led to localized conclusions. Third, the differences in the construction level and operational efficiency of data trading platforms in different regions were not fully quantified, which may affect the robustness of the conclusions. Simultaneously, because of the differences in economic systems across countries, selecting research samples solely from China may have limited the generalizability of the findings to a global context. Fourth, potential biases in company annual reports and differences in terminology usage may have affected the accuracy of the digital transformation proxy variables.

Future research could further expand the sample's scope to include more unlisted and diverse-sized manufacturing enterprises, providing a more comprehensive reflection of both the universality and differences in the impact of marketization of data elements on digital transformation. By extending the time horizon, future studies may reveal the long-term effects and dynamic evolution patterns of the marketization of data elements. Additionally, incorporating richer microlevel data, such as details on enterprise technology applications, operational models, and data ecosystems, would help provide a deeper analysis of the specific impact pathways of the marketization of data elements on internal business operations. In terms of regional heterogeneity, future research could develop a quantitative indicator system to explore how the governance quality, policy environment, and market maturity of data trading platforms in different regions influence their role in driving enterprise digital transformation. Coupled with changes in the external economic environment and international data circulation regulations, a more adaptive theoretical

framework could be proposed. International comparisons will broaden the research perspective, and future work could extend the study to other countries to explore the global applicability of marketization of data elements and their unique role in different economic systems. Moreover, future studies could also integrate multisource data, such as corporate patent data, public opinion data, and industrial IoT data, to build more accurate indicators for measuring digital transformation, thus enhancing the robustness and credibility of the findings.

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Appendix A

Table A1. Variable build instructions.

Variable Type	Variable	Variable Measurement	References
Dependent Variable	The Degree of the Digital Transformation of Enterprises (digital)	The degree of digital transformation (digital) of enterprises was measured using the frequency counts of digital transformation feature words such as artificial intelligence technology, big data technology, cloud computing technology, blockchain technology, and the application of digital technology involved in the annual reports of listed manufacturing companies. This study used the natural logarithm of word frequency as a proxy variable for enterprise digital transformation.	Wu et al. (2021); Ren et al. (2023); and Li et al. (2023) [33–35]
Independent Variable	The Marketization of Data Elements (did)	If a city established a government-led data trading platform in that year, the value of did was assigned to 1; otherwise, it was assigned to 0.	Liu et al. (2022) [31]
Control Variable	Firm Age (FirmA)	Ln(year − year of establishment + 1).	Han and Yang (2024); Soedaryono and Riduifana (2013); Pelcher (2019); Capello and Lenzi (2019) [41–44]
	Board Size (BoardS)	Ln(number of board members).	
	Average Age of Management (ManAge)	The average age of all directors, supervisors, and senior management of the company. Those whose ages were not disclosed do not participate in the calculation.	
	Fixed Asset Ratio (FixAsset)	Net fixed assets/total assets.	
	Corporate Tax Rate (Tax)	Gross income tax/profits.	
	Earnings Volatility (EarningsV)	(Earnings before interest and taxes/total assets)three-year volatility; where the three-year volatility calculation was standard deviation from year t − 2 to year t.	
	Regional Per Capita GDP Growth Rate (RGDP)	(Per capita GDP of the current year − per capita GDP of the previous year)/per capita GDP of the previous year.	
	Regional Natural Population Growth Rate (PopGrow)	(Number of births in a year − number of deaths in a year)/annual average population × 1000‰.	
	Regional Urbanization Rate (Urban)	Permanent urban population/total permanent population × 100%.	
	Regional Industrial Structure (IndusStruc)	$\sum Indu_i \times i (1 \leq i \leq 3)$, where $Indu_i$ is the value-added share of industry i.	

Table A1. *Cont.*

Variable Type	Variable	Variable Measurement	References
Mediator Variable	Management Expense Ratio (ManExpenceR)	Administrative expenses/revenue.	Han and Yang (2024) [41]
	Sales Expense Ratio (SelExpenseR)	Selling expenses/main business income.	Wu et al. (2015) [47]
	Financing Constraints (FC)	1. A model was established to measure the degree of corporate financing constraints: $P(QUFC = 1 \text{ or } 0 \mid Z_{i,t}) = \frac{e^{Z_{i,t}}}{1+e^{Z_{i,t}}}$ $Z_{i,t} = \alpha_0 + \alpha_1 size_{i,t} + \alpha_2 lev_{i,t} + \alpha_3 \left(\frac{CashDiv}{ta}\right)_{i,t} + \alpha_4 MB_{i,t} + \alpha_5 \left(\frac{NWC}{ta}\right)_{i,t} + \alpha_6 \left(\frac{EBIT}{ta}\right)_{i,t}$ (size: represents the scale of enterprise assets, the natural logarithm of total assets; lev: represents the financial leverage ratio of the enterprise, the debt-to-asset ratio = total liabilities/total assets; CashDiv: the cash dividend distributed by the company in the current year; MB: represents the price-to-book ratio of the enterprise = market value/book value; NWC: net working capital = working capital − monetary funds − short-term investment; EBIT: earnings before interest and taxes; ta: total assets). 2. The three variables of company size, company age, and cash dividend payout ratio by year were standardized $(y_i = \frac{x_i - \bar{x}}{s}, \bar{x} = \frac{1}{n}\sum_n^1 x_i, s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2})$, and then the listed companies were ranked based on the mean of the standardized variables (in ascending order). The upper and lower third quartiles were used as the dividing points for financing constraints, and the financing constraint dummy variable QUFC was determined. Listed companies above the 66th percentile were defined as the low-financing-constraint group, with QUFC = 0, and those below the 33rd percentile were defined as the high-financing-constraint group, with QUFC = 1. 3. A Logit regression was conducted on model (1) to fit the probability P of financing constraints occurring for each company in each year; this was defind as as the financing constraint index FC (with values ranging from 0 to 1).	Hadlock and Pierce (2009) [52]; Zhang et al. (2017) [53]
	Digital Technology Innovation (Dtech)	Ln(number of digital economy patent applications in a city+1).	Sun et al.'s (2022) [48]
	Clustering of Digital Services (Dsa)	The location entropy index of the number of employees in the information transmission, software, and information technology services industry.	Zhao et al. (2024) [50]

Appendix B

Table A2. Data source list.

Data Source	Access Address
China Stock Market and Accounting Research Database (CSMAR)	https://data.csmar.com/, accessed on accessed on 17 January 2025
China Research Data Service Platform (CNRDS)	https://www.cnrds.com, accessed on accessed on 17 January 2025
China Urban Statistical Yearbook	https://cnki.istiz.org.cn/csydmirror, accessed on accessed on 17 January 2025
provincial statistical yearbooks	
corporate annual reports	Company Website

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