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HOW DOES DATA FACTOR MARKETIZATION EMPOWER ENTERPRISES' NEW QUALITY PRODUCTIVITY? THE MODERATING ROLE OF EXPORT TECHNOLOGY SOPHISTICATION

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Abstract: *Advancing the marketization of data factors constitutes a critical pathway for cultivating new quality productivity. Leveraging matched city- and listed firm-level data from China (2012–2022) and employing the establishment of data trading platforms as a quasi-natural experiment, this study systematically examines the impact of data factor marketization on enterprise new quality productivity using a multi-period difference-in-differences (DID) model. The findings reveal that data factor marketization significantly enhances enterprise new quality productivity, a conclusion that remains robust after parallel trend tests, placebo tests, and propensity score matching (PSM) analyses. Moderating effect analysis demonstrates that export technology sophistication exerts a significant positive regulatory influence on the productivity-enabling effects of data factors, with the policy impact being stronger for firms with high export technology sophistication compared to those with low complexity. Heterogeneity tests further uncover differentiated policy effects: the impacts are more pronounced in eastern regions than in western regions, stronger for technology- and labor-intensive enterprises than for asset-intensive ones, and greater for large-scale enterprises than for small- and medium-sized firms. These findings provide empirical support for constructing a data factor marketization reform path characterized by "technology threshold adaptation, regional gradient advancement, and scale-specific policy implementation," offering critical insights for refining the hierarchical allocation mechanism of data factors.*

Key words: *data factor marketization, enterprise new quality productivity, export technology sophistication, multi-period DID approach*

***JEL classification**: M20*

1. INTRODUCTION

As the digital transformation of the global economy deepens, data has emerged as the fifth largest factor of production, following land, labor, capital, and technology. The market-based allocation of data plays a crucial role in promoting enterprise innovation and enhancing productivity (Jones & Tonetti, 2020). According to a report by the International Data Corporation (IDC), the total amount of global data is expected to reach 44 zettabytes (ZB) by 2024, with China's data volume accounting for approximately 20% of the global total. This figure is projected to increase to 175 ZB by 2025, further emphasizing the growing importance of data as a production factor. The Chinese government places significant emphasis on the marketization of data elements, having issued a series of policies, such as the "Opinions on Building a Data-Based System and Better Utilizing the Role of Data Elements." Additionally, it has established data trading platforms globally to promote the market allocation of data. In this context, enterprises face new opportunities and challenges, making it essential to leverage data elements to enhance quality productivity for business development.

Currently, the global industrial chain is undergoing profound restructuring, with technical barriers and the digital divide intensifying the complexity of enterprises' participation in international competition. Improving firms' quality productivity relies not only on the input of data factors but also on the transformation of these data resources into differentiated competitive advantages through the accumulation of sophisticated technological capabilities (Gereffi, 2014). The level of complexity in export technology directly reflects an enterprise's ability to integrate advanced technologies and embed high value-added components (Hausmann et al., 2007). The synergistic effect between this technological complexity and the marketization of data factors could become a key pathway to overcoming the "low-end lock-in" phenomenon. In this context, export technological complexity, an important indicator of firms' technological capabilities and their positions in global value chains, may significantly moderate the enabling effect of data factor marketization. Uncovering this regulatory mechanism is not only a pressing theoretical concern but also a practical need for China in realizing its "dual circulation" strategy.

Existing literature has made some progress in understanding the relationship between data factor marketization and firms' quality productivity. Some scholars have noted from a macro perspective that data trading platforms can significantly enhance regional total factor productivity by promoting market integration and reducing transaction costs (Li Xiaolong & Wei Qifan, 2024). In contrast, micro-level studies have shown that the marketization of data factors can drive productivity growth by accelerating the digital transformation of enterprises and optimizing resource allocation efficiency (Zheng Guoqiang, 2024). However, most studies treat data factors as independent drivers, overlooking the possibility that their effects may be constrained by firms' technological capabilities. Although some literature has briefly mentioned the heterogeneous effects of technological endowments (Su et al., 2024), a systematic analysis of the moderating role of export technological complexity in the "data-productivity" chain is still lacking. In international studies, Melitz's (2003) theory on the trade of heterogeneous firms emphasizes the impact of technological differences on export behavior yet fails to incorporate the marketization process of data factors, making it difficult to explain the new patterns of competition in the digital era.

Therefore, this study aims to explore in depth how data factor marketization empowers firms' quality productivity and the moderating effect of export technological complexity in this process. The contributions of this paper are as follows: At the theoretical level, it transcends the traditional analytical framework of production factors by constructing, for the first time, a mechanism through which data factor marketization operates under the regulation of export technological complexity. It reveals how differences in technological capabilities affect the efficiency of productivity transformation of data factors, providing a new perspective for understanding the synergy between "technology" and "data." Methodologically, we innovatively treat the establishment of data trading platforms as a quasi-natural experiment and develop a multi-period difference-in-differences model to identify the net effect of data factor marketization. We also explore the paths of heterogeneity through testing the moderating effects, offering a new econometric solution to the challenges of data factor measurement. Practically, the study systematically demonstrates the differentiated regulation based on regional levels of digitalization and industry technological attributes, proposing a policy optimization path of "gradient promotion and classification" to provide theoretical support for the government in formulating precise data factor allocation policies. Through these explorations, this study seeks to provide new theoretical perspectives and practical insights for global competition in the digital economy era.

2. LITERATURE REVIEW AND THEORETICAL ANALYSIS

2.1 LITERATURE REVIEW

As the digital economy becomes a new engine for global economic growth, the reshaping of productivity through the market-based allocation of data factors has garnered significant attention. Classical studies suggest that the non-competitive nature and increasing returns to scale associated with data factors can challenge the traditional law of diminishing returns in production (Jones & Tonetti, 2020). However, the realization of their value is highly dependent on institutional design and technological application contexts.In recent years, China has promoted the transformation of data factors from "resources" to "assets" by establishing data trading platforms and enhancing the data property rights system (Fu, Dongping, et al., 2025). Domestic scholars have further verified the role of data elements at the micro-enterprise level. For instance, Xie Kang et al. (2020) found that data factors facilitate digital transformation in enterprises, enhancing the intelligence of production processes and improving supply chain synergy. Similarly, Zheng Guoqiang (2024) demonstrated that data trading platforms can significantly boost enterprise productivity by alleviating financing constraints and reducing operating costs, as viewed from a total factor productivity perspective.Despite the insights from existing studies, most focus on the independent effects of data factors, neglecting the potential moderating role of firm heterogeneity, particularly the dynamic impact of varying technological capabilities on data empowerment effects.

Enhancing the new quality productivity of enterprises relies on the synergistic innovation of technology, organization, and factors, where the deep integration of data factors with traditional elements is seen as a core strategy for reconfiguring production functions (Lu, 2023). Existing research has examined the driving mechanisms of new quality productivity from technological innovation, organizational change, and factor upgrading dimensions, yet a systematic analysis of how data factor marketization generates heterogeneous effects through differences in technological capabilities is still lacking.Cross-country comparative studies have shown that the application of high-complexity technologies is crucial for breaking through "low-end lock-in" and achieving significant productivity improvements (Hausmann et al., 2007). The role of export technological complexity, a core indicator of firms' technological capabilities and their positioning in global value chains (GVCs), has been widely explored in the field of international trade. For instance, Melitz's (2003) theory on heterogeneous firms emphasizes the critical impact of technological differences on export behavior. However, most studies remain entrenched in traditional production factor frameworks and fail to fully incorporate the marketization process of data factors. Recent research has begun to highlight the moderating role of technological complexity in digital transformation. For example, Su, Zhiwen et al. (2024) found that high-technology firms are more likely to optimize their organizational operations through the integration of data factors. Additionally, Xiao, Peng et al. (2024) point out that the productivity-enhancing effects of digital industry agglomeration are more pronounced among firms with greater technological complexity.

Nonetheless, existing literature has notable shortcomings: first, research on data factor marketization often emphasizes either macro effects or singular micro-mechanisms, lacking a systematic approach to constructing a synergistic framework of "system-technology-capability." Second, the analysis of new quality productivity driving mechanisms has not been adequately integrated into a global context, particularly overlooking the moderating role of export technology complexity on data empowerment. Third, empirical tests of the interaction pathways between technological complexity and data factors, such as technology absorption and value chain upgrading, are still insufficient. This paper aims to address these gaps by revealing how export technological complexity amplifies the enabling effects of data elements on firms' new quality productivity through capability accumulation and network synergy.

2.2 THEORETICAL ANALYSIS

2.2.1 The impact of market-based allocation of data elements on the new quality productivity of firms

Based on the theory of the three elements of productivity, data factors drive productivity leaps by reconfiguring the combination of labor, means of labor, and objects of labor. First, in the dimension of labor, the marketization of data factors facilitates the flow of talent by aligning supply and demand in the labor market, thereby attracting highly skilled digital professionals (Acemoglu & Restrepo, 2018). This process is further enhanced by data-driven training systems that improve the skill alignment of employees (Liu, Mao, et al., 2018). Second, regarding the means of labor, data elements promote the advancement of production tools toward intelligent systems. For instance, industrial big data enables predictive maintenance of equipment (Brynjolfsson & McElheran, 2016), while Internet of Things (IoT) technologies facilitate "digital twin" simulations for optimization (Cai Weiming et al., 2022). Third, in terms of labor objects, data elements transcend the physical boundaries of traditional production factors, giving rise to new types of labor objects, such as data products and digital services. Additionally, green technological innovations achieve a dual upgrade of "digital and low-carbon" capabilities (Tian Xiujuan et al., 2022). Overall, the marketization of data factors significantly enhances the new quality productivity of enterprises by optimizing labor structures, upgrading production tools, and expanding labor objects. Therefore, this paper proposes the following hypothesis:

H1: The market-based allocation of data factors can significantly enhance the level of new quality productivity in enterprises.

2.2.2 Moderating effects of export technological complexity

According to the absorptive capacity theory (Cohen & Levinthal, 1990), firms must possess a pre-existing knowledge base to effectively leverage external resources. Enterprises with high export technology complexity, having engaged in international technological competition for extended periods, have developed the ability to decode complex technologies. They can effectively transform tacit knowledge contained in data elements (such as process parameters and R&D pathways) into innovative outputs (Su, Zhiwen et al., 2024). For instance, semiconductor companies can precisely optimize their chip design processes by analyzing global supply chain data, while firms with lower complexity may only be capable of basic data replication due to insufficient technical expertise. Moreover, global value chain theory (Gereffi, 2014) indicates that high-complexity firms can reconfigure the international division of labor using data elements. This may involve adjusting product strategies based on real-time market demand data or enhancing cross-border response efficiency through digital supply chain management systems, such as smart logistics. Based on these insights, we propose the following hypothesis:

H2: Export technological complexity positively moderates the relationship between data factor marketization and firms' new quality productivity, with stronger data-enabling effects observed in high-complexity firms.

3. RESEARCH DESIGN

3.1 MODEL SETUP

Considering that there are sequential differences in the establishment of data trading platforms in various cities, i.e., the marketization of data elements in various regions is carried out gradually, this paper adopts the progressive double-difference model for analysis. Compared with the general double-difference model, the progressive double-difference model allows the treatment effect to appear gradually in time, and takes into account the time-dynamic feature, which can better assess the actual effect of the policy.

To verify H1, the model is set as follows:

$$NQP_{ict}=a_0+a_1DID_{ct}+a_2X_{ict}+\varphi_i+\varphi_c+\varphi_t+\varepsilon_{it}$$

To verify H2, the model is set up as follows:

$$NQP_{ict}=\beta_0+\beta_1DID_{it}+\beta_2(DID_{ct}\times EXPY_i)+\beta_3X_{ict}+\varphi_i+\varphi_c+\varphi_t+\varepsilon_{it}$$

i,c,t represent firms, cities and time respectively, NQPict is the explanatory variable firms' new quality productivity, and DIDct is the core explanatory variable, which represents the net effect of policy implementation. DID takes 1 if city c establishes a data trading platform at time t, and 0 otherwise. EXPYi is the moderating variable export technological complexity, Xict represents a series of control variables, φi, φc, and φt represent the individual, city, and time fixed effects, respectively, and εit is the random error term.

3.2 DESCRIPTION OF VARIABLES

3.2.1 Explained variable: Firms' new quality productivity (NQPICT)

Based on the measurement framework of Song Jia et al. (2024), this study constructs the index system of new quality productivity of enterprises according to the theory of two factors of productivity. The specific implementation path is as follows: firstly, strategic emerging industries and future industries are selected as the research samples, as they focus on the core characteristics of new quality productivity. In terms of indicator design, productivity is decomposed into two main factors: labor and production tools - the former is subdivided into live labor (R&D staff salary, staff structure, and high education) and physical labor (fixed assets and manufacturing costs), and the latter is divided into hard technology (R&D investment, depreciation and amortization, rental expenses and intangible assets) and soft technology (total assets). share) and soft technology (total asset turnover and inverse equity multiplier). Especially for the trend of machine substitution in high-end equipment manufacturing industry, the weight of manufacturing cost ratio indicator is strengthened; at the same time, the inverse of equity multiplier conversion processing is adopted to unify the financial risk indicators into a positive measure. Finally, the weight of each indicator is calculated through the entropy value method to form the comprehensive index of enterprise's new quality productivity (for details, see the definition of indicators and the results of weight allocation in Table 1). This method not only continues the classical theoretical framework, but also enhances the explanatory power of the measurement system for emerging industries through innovative treatments such as manufacturing cost enhancement and indicator direction correction.

Table 1 System of new quality productivity indicators for enterprises

considerations	subfactor	norm	Description of indicator values	weights
labor force	labor	Percentage of R&D salaries	Research and development expenses - salaries and wages/operating income	28
		Percentage of R&D staff	Number of R&D staff / Number of employees	4
		Percentage of highly educated personnel	Number of undergraduates and above / Number of employees	3
	materialized labor (objects of labor)	Fixed assets as a percentage	Fixed assets/total assets	2
		Manufacturing costs as a percentage	(Subtotal of cash outflows from operating activities + depreciation of fixed assets + amortization of intangible assets + provision for impairment - cash paid for purchases of goods and services - wages paid to and for employees)/(Subtotal of cash outflows from operating activities + depreciation of fixed assets + amortization of intangible assets + provision for impairment)	1
production tool	hard technology	R&D depreciation and amortization as a percentage of	R&D depreciation - amortization of depreciation/operating income	27
		R&D lease payments as a percentage of	Research and development expenses - lease payments/operating income	2
		R&D direct investment as a percentage	R&D expenses - direct inputs/operating income	28
		Intangible assets as a percentage	Intangible assets/total assets	3
	soft technology	Total asset turnover	Operating income/average total assets	1
		Inverse equity multiplier	Owners' equity/total assets	1
new mass productivity				100

3.2.2 Core explanatory variable: Marketization of data elements (DID_{CT})

Drawing on the studies of Liu Manfeng et al. (2022) and Xu Ye et al. (2024), the establishment of urban data trading platforms is used as a proxy variable for data factor marketization. DIDct = 1 if the city where the firm is located establishes a data trading platform (e.g., Guiyang Big Data Exchange, Beijing International Big Data Exchange) in year t. Otherwise, it is 0. Information on platform establishment is manually collected and cross-validated through public government documents and news reports.

3.2.3 moderator variable: Export technical complexity ($EXPY_I$)

In this paper, the export technology complexity is calculated as follows:
First, drawing on Hausmann et al. (2007), the technical complexity of exports for specific product q is measured:

$$PRODY_q = \sum_k \frac{x_{kq}/X_k}{\sum_k x_{kq}/X_k} pkgdp_k$$

where q denotes a HS96-coded product, c represents a country or a region, Xcq denotes the export value of product q of country or region k, X_k is the total export value of country or region k, and pkgdpc denotes the per capita GDP level of country or region k. Secondly, referring to Zhou Shen (2006), the HS96 code is transformed into the National Economic Industry Classification 2-digit code. Then, according to the following equation, the technical complexity of export products at the industry level is calculated:

$$EXPY_{KJ} = \sum_q \frac{x_{jq}}{X_{kj}} PRODY_q$$

where, $\frac{x_{jq}}{X_{kj}}$ denotes the proportion of exports of product q of industry j in country k to the total exports of industry j in country k. Finally, referring to the idea of Gao Xiang and Yuan Kaihua (2020), total factor productivity is used to adjust the technical complexity of industry exports, so as to obtain the technical complexity of firms' exports, which is calculated as:

$$EXPY_i = \frac{TFP_i}{TFP_j} EXPY_{kj}$$

where EXPYi is the export technological complexity of firm i. Total factor productivity (TFP) is calculated by LP method with reference to Lu and Lian Yujun (2012).

3.2.4 Control variables

In order to further improve the regression accuracy of the empirical evidence, this paper refers to the relevant literature to incorporate the following control variables: enterprise size, gearing ratio, net profit margin of total assets, proportion of fixed assets, proportion of management shareholding, proportion of shareholding of the top five shareholders, and years of establishment of the company. The specific calculations are as follows:

Table 2 Breakdown of control variables

control variable	variable name	calculation method
Size	Enterprise size	ln (total assets)
Lev	gearing	Total liabilities/total assets
ROA	Net profit margin on total assets	Net profit/total assets
FIXED	Fixed assets as a percentage	Net fixed assets/total assets
Mshare	Management shareholding	Management shareholding data divided by total share capital
TOP5	Shareholding ratio of top five shareholders	Number of shares held by top five shareholders/total shares
Firmage	Years of Establishment	ln(current year - year of incorporation + 1)

3.3 DATA SOURCES

This paper takes Chinese A-share listed companies as the research sample, and the sample time span is 2012-2022. The enterprise data comes from the CSMAR database, and the data trading platform data comes from the Big Data White Paper 2021 published by the China ICT Institute and the public information on the websites of data trading platforms in various cities. In order to ensure the stability of the results, the data in this paper are processed as follows (1) ST enterprises are excluded; (2) samples of companies that have been delisted are excluded; and (3) samples of companies with more missing sample values are excluded. All variables were subjected to 1% tailing.

4. EMPIRICAL RESULTS AND ANALYSIS

4.1 ANALYSIS OF BENCHMARK REGRESSION RESULTS

Table 3 illustrates the impact of data factor marketization on firms' new quality productivity. Columns (1) through (8) present the regression results, which progressively incorporate control variables and fixed effects. The positive coefficient of the core explanatory variable, DID, indicates that the establishment of urban data trading platforms significantly enhances the level of new quality productivity in enterprises, supporting research hypothesis H1. Specifically, the marketization of data factors improves enterprises' access to high-quality data by facilitating data sharing and circulation. This, in turn, accelerates their technological innovations and the digitization of production processes (Fu, Dongping et al., 2025). Furthermore, the DID coefficient remains significantly positive even after controlling for variables such as enterprise size, age, and gearing ratio, demonstrating the robustness of the positive impact of data factor marketization. These findings align with the conclusions drawn by Zheng Guoqiang (2024), who also reported that the implementation of data trading platforms significantly boosts productivity by enhancing resource allocation efficiencies. This correspondence with existing literature reinforces the validity of our results and underscores the importance of data factor marketization for improving new quality productivity.

Table 3 Benchmark regression results

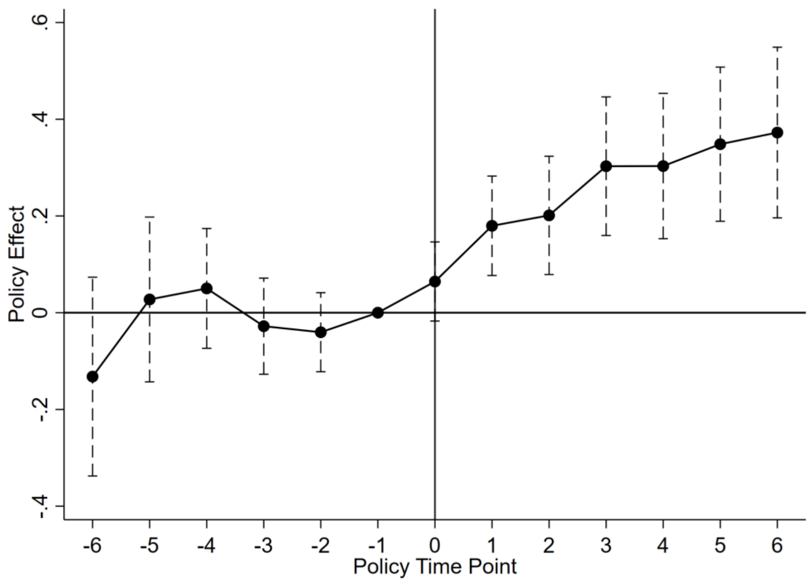
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	New Quality Productivity							
DID	0.215***	0.209***	0.201***	0.202***	0.196***	0.199***	0.199***	0.203***
	(3.524)	(3.427)	(3.306)	(3.330)	(3.237)	(3.302)	(3.322)	(3.714)
Size		0.096*	0.054	0.059	0.101*	0.094*	0.115**	0.282***
		(1.927)	(1.031)	(1.139)	(1.904)	(1.776)	(2.171)	(6.088)
Lev			0.630***	0.596***	0.281	0.188	0.120	-0.261
			(3.623)	(3.465)	(1.520)	(1.021)	(0.653)	(-1.598)
Mshare				-0.010***	-0.009***	-0.007***	-0.005***	-0.005**
				(-5.127)	(-4.753)	(-3.774)	(-2.582)	(-2.490)
ROA					-1.455***	-1.471***	-1.406***	-0.537***
					(-7.224)	(-7.301)	(-7.046)	(-3.216)
FirmAge						1.260***	0.990***	0.707**
						(4.027)	(3.113)	(2.432)
Top5							-1.058***	-0.813***
							(-3.955)	(-3.302)
FIXED								8.296***
								(28.244)
_cons	5.048***	2.916***	3.590***	3.613***	2.868**	-0.668	0.212	-4.406***
	(263.008)	(2.635)	(3.161)	(3.186)	(2.493)	(-0.494)	(0.153)	(-3.647)
fixed effect	containment	containment	containment	containment	containment	containment	containment	containment
N	33308	33308	33308	32402	32401	32389	32389	32389
R2	0.798	0.799	0.799	0.802	0.803	0.804	0.804	0.845
Adj.R2	0.767	0.768	0.768	0.771	0.772	0.773	0.773	0.820

*Note: ***, **, and * indicate significant at the 1%, 5%, and 10% levels, respectively; same table below*

4.2 PARALLEL TREND TEST

Before applying the double-difference approach to examine the causal link between data factor market construction and the development of new quality productivity, the parallel trend assumption needs to be satisfied. Therefore, this paper takes the first year of the pilot as the base period and draws on previous studies to test whether this assumption is valid using event analysis. From the results, we show that before the establishment of the data trading platform, there is no significant difference in the level of new quality productivity between the treatment group and the control group firms, and the coefficient estimates always fluctuate around the zero value and the confidence intervals contain zeros, which satisfies the parallel trend hypothesis, indicating that the exogeneity of the experimental group selection and policy shocks is in line with the requirements of the empirical design. In the year of policy implementation, the coefficient is positive but does not pass the significance test, probably because the initial construction of the data trading platform is still in the exploratory stage, the scale of data circulation is limited and enterprises need time to adapt to the new rules. In the first two years after the implementation of the policy, the coefficient gradually rises to 0.15 and 0.23, indicating that the productivity enhancement effect of data factor marketization has a lag and persistence. This phenomenon can be attributed to the accumulation effect of data elements: with the improvement of trading platform rules and the deepening of data resources integration, enterprises gradually optimize their data parsing capabilities and technical application scenarios, and ultimately achieve a leap in productivity (Fu, Dongping, et al., 2025). With the advancement of the policy, the marketization effect of data elements gradually appears: in the third year of policy implementation, the coefficient reaches a peak and is significantly positive, indicating that the maturity of the data sharing mechanism and the release of technological synergies have significantly enhanced the new quality productivity of enterprises. In the long run, the policy effect tends to stabilize in the late stage, reflecting that the allocation efficiency of data factors may be close to the equilibrium state, or subject to the law of diminishing marginal returns. In summary, the results of the parallel trend test verify the dynamic empowering effect of data factor marketization on enterprise productivity, and provide empirical evidence for the continuous improvement of the data trading system and the deepening of factor marketization reform.

***Figure 1** Parallel trend test*



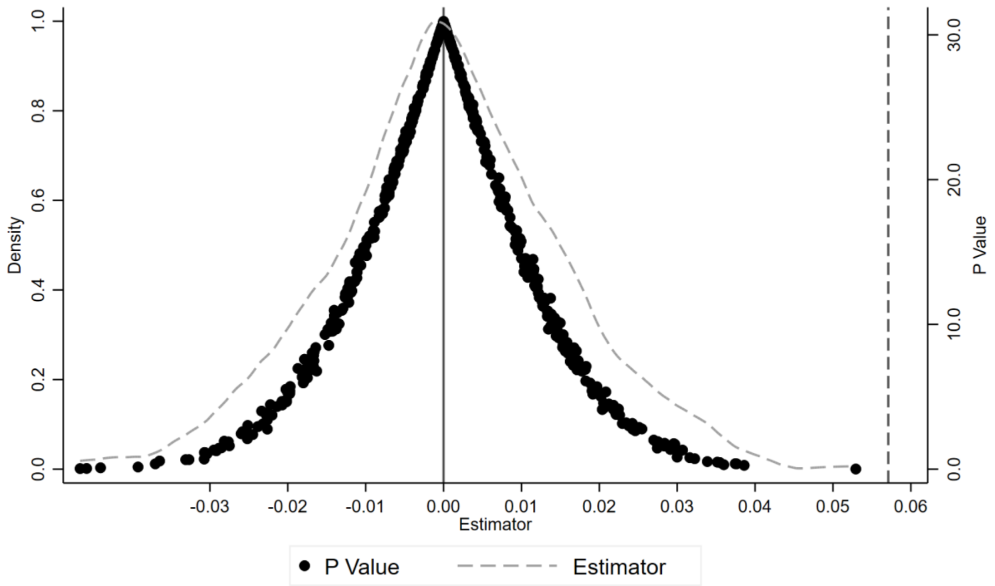
4.3 ROBUSTNESS TESTS AND ENDOGENEITY TREATMENT

4.3.1 Placebo test

To verify the robustness of the benchmark regression results, this paper repeats the simulation of 500 pseudo-policy shocks by randomly assigning treatment groups to placebo tests. Figure 2 illustrates the kernel density distribution of the pseudo-treatment effect (Estimator) and its corresponding p-value. The results show that the pseudo-treatment effect coefficients are highly concentrated around the zero value (mean = -0.002, standard deviation = 0.008) and 95% of the estimates are distributed in the interval [-0.018, 0.014], suggesting that randomly-generated pseudo-policies do not have any systematic effect on productivity. The coefficient of the true policy effect (0.057) is located in the right tail of the pseudo-effect distribution (only 1.2% of the simulated values are larger than the true values) and significantly deviates from the random noise interval, confirming that the productivity-enhancing effect of data factor marketization is not accidental. In addition, the p-value distribution shows that more than 95% of the simulation results fail the 5% significance level test, further supporting the reliability of the benchmark findings.

This result suggests that the empirical design of this paper effectively avoids the problems of selectivity bias and endogeneity, and provides robust evidence of the policy effects of data factor marketization reform.

Figure 2 Placebo test



4.3.2 PSM-DID

The validity of the multi-temporal double-difference model (DID) relies on the assumption that the variables characterizing the experimental and control groups prior to policy implementation satisfy a common trend. If the two groups are systematically different, the estimation results may be biased.

To mitigate the selectivity bias, this paper uses the propensity score matching (PSM) method to carry out robustness tests to ensure that the regression results are realistic and reliable. Column (1) of Table 4 presents the PSM-DID regression results.

The coefficient of the core variable DID is 0.205 and significant at the 1% level, which is highly close to the main regression results and confirms the robustness of the policy effects.

The direction and significance of the other control variables are also consistent with the main regression. In summary, the PSM-DID test results indicate that the estimation of the policy effect has good robustness.

4.3.3 Joint industry-year fixed effects

To rule out the interference of heterogeneous shocks at the industry level over time (e.g., cycles of technological change, industry policy adjustments) on the estimation results, this paper further controls for joint industry-year fixed effects.

The results in column (2) of Table 4 show that the core variable DID is significant at the 5% level, which is highly consistent with the direction and magnitude of the benchmark regression results.

Despite a slight drop in the significance level, the stability of the coefficients suggests that the productivity-enhancing effects of data factor marketization do not stem from industry-specific time trends (e.g., certain industries naturally have data integration advantages or cyclical technological upgrades), but rather are institutionalized by the policy itself.

The joint industry-year fixed effects further strip away potential confounding of policy effects with industry dynamics by absorbing industry-year heterogeneity (e.g., the difference between rapid iteration in the information technology industry and gradual transformation in traditional manufacturing), enhancing the credibility of the findings

Table 4 *Robustness test*

	(1)	(2)
	PSM-DID	Joint industry-year fixed effects
DID	0.205***	0.132**
	(3.626)	(2.520)
Size	0.289***	0.224***
	(5.711)	(4.958)
Lev	-0.385**	-0.342**
	(-2.236)	(-2.137)
Mshare	-0.006***	-0.003
	(-2.608)	(-1.603)
ROA	-0.616***	-0.472***
	(-2.931)	(-2.875)
FirmAge	0.771**	0.754***
	(2.536)	(2.797)
Top5	-0.836***	-0.502**
	(-3.249)	(-2.135)
FIXED	8.383***	8.335***
	(28.836)	(29.748)
_cons	-4.727***	-3.396***
	(-3.633)	(-2.918)
fixed effect	containment	containment
N	25352	32389
R2	0.852	0.851
Adj. R2	0.823	0.827

4.4 ANALYSIS OF MODERATING EFFECTS

Table 5 reports the regression results with firms' export technological sophistication as the moderating variable. The coefficient of the core explanatory variable DID (Data Factor Marketization Policy) is 0.228, which is significant at the 1% level, indicating the robust existence of a positive policy contribution to firms' new quality productivity. The coefficient of the cross-multiplier term of the moderating variable export technological complexity with DID is significantly positive, indicating that export technological complexity significantly enhances the enabling effect of data factor marketization. Specifically, firms with higher export technological complexity are more capable of using data factors to optimize production processes and integrate innovation resources, thus releasing policy dividends more fully.

Table 5 *Moderated effects test results*

	(1)
	New Quality Productivity 1000
DID	0.228***
	(3.791)
DID*EXPY	0.018***
	(3.416)
EXPY	0.011***
	(3.008)
Size	0.202***
	(3.460)

Lev	-0.203
	(-1.116)
Mshare	-0.002
	(-0.898)
ROA	-0.392**
	(-2.165)
FirmAge	0.471
	(1.413)
Top5	0.029
	(0.109)
FIXED	8.951***
	(42.424)
_cons	-2.677*
	(-1.862)
fixed effect	containment
N	18995
R2	0.863
Adj. R2	0.838

4.5 HETEROGENEITY ANALYSIS

Table 6 Heterogeneity test

	(1) eastern part	(2) Central Region	(3) Western Region	(4) labor-intensive	(5) asset-intensive	(6) technology-intensive	(7) Large-scale enterprises	(8) Non-large-scale enterprises
DID*EXPY	0.0165***	0.0462***	0.0134	0.0260***	-0.0041	0.0193***	0.0237***	0.0063
	(2.973)	(3.419)	(1.421)	(2.662)	(-0.365)	(3.460)	(3.543)	(0.819)
control variable	contain.	contain.	contain.	contain.	contain.	contain.	contain.	contain.
fixed effect	contain.	contain.	contain.	contain.	contain.	contain.	contain.	contain.
N	11920	2025	2625	3495	3058	9938	10472	8252
R2	0.899	0.848	0.909	0.886	0.893	0.899	0.885	0.874
Adj. R2	0.878	0.812	0.886	0.856	0.862	0.876	0.860	0.837

In order to explore whether the moderating effect of export technology complexity in the new quality productivity of enterprises empowered by data factor marketization is universal, this paper carries out heterogeneity tests from the dimensions of region, industry and enterprise size. At the theoretical level, the intensity of the moderating effect may be constrained by regional resource endowment, industry technological attributes and enterprise resource integration capacity. For example, the eastern region, relying on mature digital infrastructure and the concentration of high-skilled talents, may be more likely to realize the synergy between technological capabilities and data elements; while technology-intensive industries may be able to transform data resources into productivity more efficiently due to their advantages in technology decoding and innovative applications.

The empirical results show that the moderating effect varies significantly across sub-samples. At the regional level, the moderating effect is significant in the eastern region, indicating that its perfect data circulation network and technological ecosystem strengthen the gain of export technological complexity on the policy effect; while the effect is not significant in the western region, probably due to the lagging of digital infrastructure and a single scenario of technological application, which restricts the synergistic paths of the data elements and technological capabilities. From the industry level, the moderating effect of technology-intensive industries is significant, confirming the core role of high-complexity technological capabilities in data analysis and innovation transformation; although the moderating effect of labor-intensive industries is significant, the limitations of technological application scenarios may lead to their actual gains being lower than that of the technology-intensive industries; the moderating effect of asset-intensive industries is insignificant and in the negative direction, reflecting their reliance on traditional capital inputs, and the marginal effect of data elements on the path dependence. path dependence, and the marginal contribution of data elements is diluted. At the level of firm size, the moderating effect of large-scale firms is significantly stronger than that of non-large-scale firms, reflecting the improvement of data integration efficiency under the economy of scale and the support of resource redundancy for the inclusiveness of technological trial and error.

This result is highly consistent with the theory of technology absorptive capacity and the theory of scale effect. First, through the long-term accumulation of technical knowledge, the eastern region and technology-intensive industries are able to efficiently transform the implicit information in data elements (e.g., market demand trends, process parameters) to optimize the innovation and value chains; second, large-scale enterprises are able to bear the cost of data-driven trial-and-error and accelerate technology iteration by virtue of the redundancy of resources and collaborative networks. In contrast, the western region is constrained by weak digital infrastructure and the path dependence of non-technology-intensive industries on traditional factors, which makes it difficult to fully unleash the moderating effect of data factors. Possible reasons include: at the regional level, the degree of marketization and digitization supporting policies in the eastern region are more complete, reducing data transaction costs and institutional friction, while the technological ecology of the western region is lagging behind, making it difficult for data resources to be embedded in the local value chain; at the industry level, technology-intensive industries are naturally equipped with complex data analysis and application scenarios, while asset-intensive industries have a solidified production process, and data empowerment requires a higher level of technological adaptation. At the industry level, technology-intensive industries are naturally equipped with complex data analysis and application scenarios, while asset-intensive industries have solidified production processes, so data empowerment needs to break through the high threshold of technology adaptation; at the enterprise level, the scale effect amplifies the regulating effect of technological capability on data elements through resource integration and risk dispersion mechanisms, while non-large-scale enterprises are limited by innovation investment and trial-and-error tolerance, which impede the regulation path.

In sum, the heterogeneity test shows that there are significant structural differences in the moderating effect of export technological sophistication, the strength of which depends on the regional level of digitization, the technological attributes of the industry and the size of the firm. This finding provides evidence of the "technology-data-productivity" synergy mechanism, suggesting that policy design needs to take into account regional and industry heterogeneity - deepening data factor marketization reforms in the eastern region with technology-intensive enterprises, and deepening data factor marketization reforms in the western region with technology-intensive enterprises. It suggests that policy design needs to take into account regional and industry heterogeneity - deepening data factor market-oriented reforms in eastern regions and technology-intensive firms, and prioritizing digital infrastructure and technical training in western regions and asset-intensive firms, in order to unleash the productivity-enhancing potential of data factors across the board.

5. RESEARCH FINDINGS AND POLICY RECOMMENDATIONS

5.1 FINDINGS

This paper systematically examines the mechanism and heterogeneity characteristics of the impact of data factor marketization on the development of firms' new-quality productivity, using matched data from Chinese cities and listed companies spanning 2012 to 2022. We employ the construction of data trading platforms as a quasi-natural experiment and apply a multi-temporal difference-in-differences model. Our findings indicate that data factor marketization significantly enhances the new quality productivity of enterprises. This conclusion remains robust even after accounting for major policy interferences, conducting placebo tests, and various robustness checks. The core mechanism at work involves optimizing factor allocation and fostering organizational innovation. Specifically, data factors attract highly skilled talent, optimize investment decisions, and accelerate technological iteration by reconfiguring the interplay of labor, capital, and technology. Additionally, intelligent management systems and supply chain synergies lower management costs and spur business innovation, ultimately facilitating a leap to higher-order productivity. Heterogeneity analysis reveals significant structural differences in the policy effects. These effects are particularly strong for enterprises in labor-intensive and technology-intensive industries. Furthermore, the realization of policy benefits is more pronounced among firms in the eastern region and larger enterprises, underscoring the moderating roles that regional development levels, industry technology attributes, and enterprise resource endowments play in influencing the effects of data empowerment.

5.2 POLICY RECOMMENDATIONS

To fully unleash the potential of data element marketization for enhancing productivity, coordinated efforts are needed in three key areas: institutional development, technical support, and differentiated policies.

First, it is essential to deepen the optimization and standardization of data trading platform functions. Each region should leverage its unique resources to establish a multi-level data circulation hub. This involves strengthening data classification, pricing, and trading capabilities, as well as exploring a traceability mechanism based on blockchain technology to ensure transaction transparency and security. Additionally, there should be a push for nationally unified data classification standards and a metadata management system to eliminate data barriers across industries and regions.

Second, consolidating the hardware foundation and technical ecosystem for data circulation is vital. This includes accelerating the deployment of 5G networks, city-level big data centers, and edge computing nodes to provide essential infrastructure for efficient data flow. Furthermore, collaboration between enterprises and universities should be encouraged to address key technologies such as privacy computing and machine learning. Supporting research and development in data mining and intelligent algorithms through tax incentives and special funds, as well as cultivating a diverse pool of digital talent, is also crucial.

Third, precise and differentiated policy interventions must be implemented. In labor-intensive industries, efforts should focus on promoting digital infrastructure and the intelligent transformation of production processes. For capital-intensive industries, guiding the integration of data elements with existing assets can optimize equipment operation and maintenance efficiency, as well as asset turnover through the use of industrial big data. In technology-intensive industries, increased support for building data science teams and fostering collaboration between industry, academia, and research institutions is necessary. This includes promoting the development of industry-level data platforms to accelerate the sharing and application of complex technical data.

By utilizing a multi-dimensional approach that fosters regional synergy (e.g., eastern technology radiating to the west), industry adaptation (focusing on breakthroughs in technology-intensive sectors), and enterprise empowerment (enabling large-scale enterprises to lead the ecosystem), we can maximize the synergistic effects of data elements and traditional resources. This will inject sustained momentum into the transformation and upgrading of enterprises in the digital economy and support the overall high-quality development of the region.

REFERENCES:

[1] Cohen W M,Levinthal D A. Absorptive Capacity: a New Perspective on Learning and Innovation[J]. Administrative Science Quarterly,1990,35(1):128-152.

[2] Fu Dongping,Wang Huan,Guo Jiedan. How can the marketized allocation of data elements enhance the new quality productivity of enterprises? --Based on the Conduction Mechanism of Enabling Urban Digital Economy Development[J]. Western Forum,2025,35(01):22-35.

[3] Gao Xiang,Yuan Kaihua. Cleaner production environmental regulation and firms' export technological sophistication--micro evidence and impact mechanisms[J]. International Trade Issues,2020,(02):93-109.DOI:10.13510/j.cnki.jit.2020.02.007.

[4] Gereffi G. Global Value Chains in a Post-Washington Consensus World[J]. Review of International Political Economy,2014,21(1):9-37.

[5] Hausmann, R., Hwang, J., & Rodrik, D. (2007). What you export matters. Journal of Economic Growth , 12 (1), 1-25.

[6] Jones B F,Tonetti C. Nonrivalry and the Economics of Data[J]. American Economic Review,2020,110(9):2819-2858.

[7] LIU Manfeng,YANG Jie,CHEN Liang. Data factor market construction and urban digital economy development[J]. Contemporary Finance and Economics,2022,(01):102-112.DOI:10.13676/j.cnki.cn36-1030/f.2022.01.010.

[8] Lu Minfeng. Data marketization empowers new quality productivity:Theoretical logic, implementation model and development trend[J/OL]. [2024-04-20]. Xinjiang Social Science,2024. http:||kns.cnki.net/kcms/detail/65.1211.F.20240219.1452.002.html

[9] LU Xiaodong,LIAN Yujun. Estimation of total factor productivity of Chinese industrial enterprises:1999-2007[J]. Economics(Quarterly),2012,11(02):541-558.DOI:10.13821/j.cnki.ceq.2012.02.013.

[10] Melitz M J. The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity[J]. Econometrica,2003,71(6):1695-1725.

[11] SONG JIA,ZHANG JINCHANG,PAN YI.A study on the impact of ESG development on firms' new quality productivity--empirical evidence from Chinese A-share listed firms[J]. Contemporary Economic Management,2024,46(06):1-11.DOI:10.13253/j.cnki.ddjjgl.2024.06.001.

[12] SU Zhiwen,LIU Ran,LIU Chuanming. Can the marketization of data factors promote the development of new quality productivity of enterprises - based on the perspective of factor allocation and organizational operation[J]. China Science and Technology Forum,2024,(12):31-43.DOI:10.13580/j.cnki.fstc.2024.12.008.

[13] Teece D J. Explicating Dynamic Capabilities: The Nature and Microfoundations of (Sustainable) Enterprise Performance[J]. Strategic Management Journal,2007,28(13):1319-1350.

[14] Xie Kang,Xia Zhenghao,Xiao Jinghua. Enterprise realization mechanism of big data becoming a real production factor: a product innovation perspective[J]. China Industrial Economy,2020,(05):42-60.DOI:10.19581/j.cnki.ciejournal.2020.05.014

[15] Xu Ye,Wang Zhichao. Data factor marketization construction and enterprise digital transformation - a quasi-natural experiment based on data trading platform[J]. Soft Science,2024,38(09):24-29+39.DOI:10.13956/j.ss.1001-8409.2024.09.04.

[16] Zhang Xiu'e, Wang Wei, Yu Yongbo. Research on the impact of digital intelligence transformation on the new quality productivity of enterprises [J/OL]. Scientific research, 1-19 [2024-06-18]. https: // doi. org/10.16192/j.cnki.1003-2053.20240518.003.

[17] Zheng Guoqiang, Zhang Xinyuan, Zhao Xinyu. How does data factor marketization drive enterprise digital transformation? [J]. Industrial Economics Research, 2023(2) :56-68.

[18] Zhou Shen. An empirical study of the impact of trade liberalization on the elasticity of demand for industrial labor in China[J]. World Economy,2006,(02):31-40+95.