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The Impact of Technological Convergence in Digital and Real Industries on the New Quality Productive Forces: Evidence from Chinese Listed Companies

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Abstract: Research Question: How does the technological convergence of digital and real industries influence the new quality productive forces in Chinese listed companies? **Motivation:** Accelerating the development of the digital economy, promoting the deep technological convergence of digital and real industries, and creating internationally competitive digital industry clusters are essential for China's development in the new era. **Idea:** Based on the financial statements and patent information of Chinese listed companies from 2013 to 2022, this study examined the impact of technological convergence in digital and real industries on the development of new quality productive forces in enterprises. **Data:** Panel data that consist of 4040 firm-year observations were analysed in this study. The data were extracted from the database of China's National Intellectual Property Administration and financial statement data of A-share listed companies for the period 2013 to 2022. **Method/Tools:** The panel regression analysis was carried out. Several robust tests are conducted such as endogeneity test, heterogeneity test and alternative measures of key variables. **Findings:** This study finds that technological convergence in digital and real industries significantly enhances the level of new quality productive forces in enterprises, and this conclusion holds true even after robustness checks and controlling for endogeneity. The heterogeneity analysis shows that the effect of technological convergence in digital and real industries on the development of new quality productive forces is more pronounced in non-manufacturing and non-high-tech industries. **Contributions:** The results provide factual support and policy implications for promoting technological convergence in digital and real industries and advancing the development of new quality productive forces in enterprises.

Keywords: Digital economy, technological convergence, new quality productive forces.
JEL Classification: O14, C23, O32

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1. Introduction

Technological convergence in digital and real industries is a process of industrial restructuring and innovation, which serves as a critical engine for promoting high-quality industrial development. Consequently, the digital economy has become a key competitive area among major economies (Zhao and Zhou, 2022). Simultaneously, the integration of the digital economy with the real economy has become China's strategic choice to reap the benefits of the latest technological and industrial revolution (Pan *et al.*, 2022). As an essential component of the digital economy, technological convergence in digital and real industries within enterprises can create higher value-added products and services, thereby providing momentum for development (Popkova *et al.*, 2022).

The global digital economy is developing continuously. According to the Global Digital Economy Development Index Report 2023, the overall development of the global digital economy has shown an upward trend, with the average TIMG index score rising from 45.33 in 2013 to 57.01 in 2021, an increase of 26 percent (Wang and Shi, 2024). In 2023, China ranked eighth in the overall TIMG index list, with the USA topping the rankings. Figure 1 shows the 2023 ranking comparison of TIMG and digital competitiveness indices for China, Singapore, United Kingdom and USA. Ranking data were sourced from the Institute of Management Development (2024) and China Daily (2023). Notably, after 2018, the catching-up trend among major countries in the digital economy became more apparent, with the global median TIMG index surpassing the global average and showing an accelerated upward trend. The rapid development of the digital economy has been primarily driven by the advancement of digital markets and construction of digital infrastructure, while improvements in digital technology and governance have been relatively slow. In terms of national disparities, the level of development of the global digital economy among countries shows a convergence trend. As a key direction in the development of the digital economy, technological convergence in digital and real industries essentially represents the empowerment and innovation of traditional industries through new elements such as technology, resources and platforms of the digital economy (Meng *et al.*, 2023).

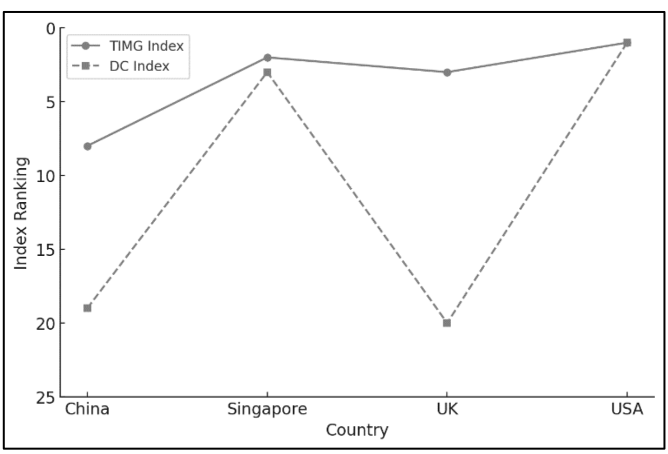

Figure 1: TIMG and digital competitive (DC) indices ranking by country

Industrial technological convergence refers to the integration of production within an industrial sector. In the era of rapid digital economic development, digital elements have become crucial production factors within industries. From a micro perspective, a significant feature of technological convergence in digital and real industries within enterprises is the integration of data with other production elements in the real industry, resulting in large-scale empowerment effects. Digital elements promote industrial integration through intelligent and automated manufacturing processes, thereby reducing production costs to meet consumer demand. These elements also eliminate the information asymmetry between producers and consumers. The trend of industrial technological convergence facilitated by digital elements, particularly business integration between traditional and digital industries, has developed significantly, disrupting traditional development concepts, business models, and industrial layouts (Huixin and Yong, 2023).

Simultaneously, productivity plays a crucial role in enterprises' high-quality development. New quality productive forces based on innovation break away from traditional economic growth methods and productivity development paths (Chen *et al.*, 2024). They are characterized by high technology, efficiency, and quality, aligning with the advanced productive forces of the new development concept. Industrial innovation has proven to be a significant factor in improving productivity, employment capabilities, and high-quality enterprise development (Bai *et al.*, 1997). Therefore, studying the impact of technological convergence in digital and real industries on the new quality productive forces of enterprises is of great practical significance for promoting high-quality economic development.

Currently, existing studies focuses primarily on theoretical aspects, with empirical studies at micro level being scarce. For example, Zhang *et al.* (2022) studied at firm-level to assess how digital transformation affects production efficiency of listed firms. This study fills the gap by providing micro-level empirical analysis based on firms' data. This study utilizes financial statement data from listed companies to empirically examine the impact and transmission mechanism of technological convergence in digital and real industries on the new quality productive forces of enterprises. Based on the research findings, policy recommendations are proposed to help enterprises accelerate the formation of new quality productive forces through technological convergence, thereby promoting high-quality economic development.

2. Literature Review

2.1 New Quality Productive Forces

The concept of new quality productive forces was proposed to describe the transformative impact of technological progress on economic growth and social development. As society continues to evolve under the influence of digitalization, the role of human labor diminishes and is replaced by the advent of robots and AI technology, leading to a shift from labor- to capital-intensive production (Szalavetz, 2022). This transformation of production systems necessitates the modernization of traditional productive forces through the integration of intelligence, technology, and innovation to ensure sustainable economic growth and improved living standards for enterprises (Popelo, 2017). Therefore, choosing new quality productive forces is conducive to promoting rapid corporate development, enabling enterprises to address the challenges posed by globalization effectively (Popkova *et al.*, 2010).

2.2 Technological Convergence in Digital and Real Industries

Technological convergence in digital and real industries refers to the integration and empowerment of advanced digital technologies with traditional industrial processes, which bring new business vitality and strong competitiveness to enterprises. This phenomenon is driven by the wave of digitalization, which provides opportunities for countries such as China to leapfrog into the digital era and restructure the global value chain (Xu and Xu, 2023). As globalized technology and industrial convergence develop, digitalization blurs industry boundaries, making them increasingly permeable and further emphasizing this convergence (Szalavetz, 2022). Merritt (2022) found that digital industry convergence will lead to a decrease in employment rates in industries such as communication, while increasing average wages. Additionally, the technological convergence of digital industries, such as 3D scanning, printing, and motion capture, offers new employment opportunities by merging the real and digital worlds and enhancing workforce quality (Rani *et al.*, 2023).

In summary, technological convergence in digital and real industries plays a crucial role in reshaping the digital economy and traditional industries, significantly affecting enterprises' productivity levels. Research has found that the integration of digital technologies, such as additive manufacturing, virtual modelling, and the industrial Internet, with traditional industries improves product quality, reduces production costs, enhances productivity quality, and ultimately increases the predictability of industrial systems (Tikhonyuk *et al.*, 2023). Particularly, in regions with optimized energy structures and moderate economic agglomeration, technological convergence in digital and real industries promotes high-quality economic development through industrial collaboration, productivity enhancement, and industrial upgrading (Dong and Li, 2022). Based on the above, this study proposes the following hypothesis:

H1: Technological convergence positively affects the new quality productive forces

3. Methodology

3.1 Data

The sample data utilized in this study are sourced from two databases. First, the Enterprise Patent Database of China's National Intellectual Property Administration, from which the enterprise invention patent-related information is selected. Financial statement data of A-share listed companies from 2013 to 2022 were chosen. There are 404 companies, resulting in 4040 firm-year observations. Although the concept of "new quality productivity" was proposed by the Chinese government in 2023, its essential connotations (technological innovation, industrial upgrading, etc.) have long been supported by relevant studies, such as Bai *et al.* (1997) and Popelo (2017). Therefore, firm-level productivity changes have accumulated over time and are not a sudden new phenomenon.

The measurement of new quality productive forces (Npro) is represented by the enterprise's new quality productive force index, developed by Song *et al.* (2024). The index was derived from weighted indicators using the entropy method. The indicators consist of labour and production tools. Labour tools include both living and materialized labour. Production tools can be divided into hard and soft technology. Hard technology is measured by the proportion of R&D investment, depreciation and amortization expenses, leasing expenses, and intangible asset proportions; while soft technology is measured by the total asset turnover ratio and reciprocal of the equity multiplier (Guo, 2025).

This study adopts the definition of technological convergence in digital and real industries from Huang and Gao (2023). Based on the Classification Table of Core Industries in the Digital Economy and Corresponding International Patent Classification (IPC) (2023) released by the National Intellectual Property Administration, digital industry technology patents are identified using IPC classification. Then, by matching patent citation information with patent publication numbers, the cited patents are determined whether they belong to digital industry technology. If the main IPC classification of a patent is not digital industry technology, and at least one of its patents is digital industry technology, it is defined as an instance of technological convergence in digital and real industries. This indicator is summed annually, and then the natural logarithm is taken after adding 1, serving as a measure of technological convergence in digital and real industries for enterprises, denoted by TechConv.

Besides that, a set of enterprise-level control variables (ContVars) is selected to control the potential influence of other factors on the empirical results. Table 1 displays a list of control variables and their measurements.

Table 1: Control variables and their measurements

Variable	Variable Name	Measurement
Company size	Size	Natural logarithm of total assets
Leverage ratio	Lev	Total liability at year-end / total assets at year-end
Return on equity	ROE	Net profit / average shareholder equity
Cash flow ratio	Cashflow	Net cash flow from operating activities / total assets
Revenue growth rate	Growth	(Operating revenue of this year / Operating revenue of last year) – 1
Profitability	Loss	Loss = 1 if net profit < 0 Loss = 0 if net profit ≥ 0
Number of directors	Board	Natural logarithm of the number of board members
Proportion of independent directors	Indep	Number of independent directors / total number of directors.
CEO-Chair duality	Dual	Dual = 1 if chairman of the board and CEO is the same person. Dual = 0 if otherwise.
Top 10 shareholders' ownership ratio	TOP10	Number of shares held by the top ten shareholders / total shares.
Tobin's Q ratio	TobinQ	(Market value of circulating shares + Non-circulating shares × Net asset value per share + Book value of liabilities) / total assets.
State ownership	SOE	SOE = 1 if the company is state-owned SOE = 0 if otherwise
Company age	FirmAge	Company Age (FirmAge): ln(Current year - Year of establishment + 1).
Big 4 audit	Big4	Big4 = 1 if the company is audited by one of the Big Four accounting firms. Big4 = 0 if otherwise

3.2 Models and Methods

The model constructed for the baseline regression, aimed at examining the impact of technological convergence in digital and real industries on enterprise new quality productive forces, is as follows:

$$Npro_{it} = \beta_0 + \beta_1 TechConv_{it} + \sum \beta_n ContVars_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{1}$$

where i and t represent enterprises and years, respectively, $Npro_{it}$ denotes the capacity of new quality productive forces of enterprise i in year t, $TechConv_{it}$ represents the quantity of technological convergence in the digital and real industries of enterprise i in year t, $ContVars_{it}$ constitutes a set of control variables, μ_i is enterprise fixed effects, γ_t is year fixed effects.

To ensure the reliability of the regression results above, robust tests are conducted. First, the instrumental variable approach is conducted to address the endogeneity issues in the regression model. The Two-Stage Least Squares (TSLS) is often employed for the estimation.

Second, the Propensity Score Matching (PSM) approach is used to address the issue on selective bias in the sample given the potential correlation between technological convergence in the digital and real industries and firm characteristics. Specifically, the sample is grouped based on whether firms engage in the integration of digital and real industries. Variables such as firm size, leverage ratio, return on equity, cash flow ratio, revenue growth rate, loss status, board size, proportion of independent directors, CEO duality, top 10 shareholder ownership, Tobin's Q, state ownership, firm age, and Big 4 status are used as covariates for matching. Additionally, a balance test was conducted on all covariates before propensity score matching. The propensity scores for this integration are estimated and then the sample is matched using the nearest-neighbor 1:1 matching based on propensity scores. Finally, the matched sample is reintroduced into the baseline model for testing.

Third, following Wu *et al.* (2021), this study employs a multi-period differences-in-differences (DID) model and further utilizes PSM-DID tests to control for endogeneity issues. Firms in the sample that have engaged in technological convergence in digital and real industries at least once during the observation period are considered the treatment group, whereas other firms serve as the control group. The double-difference model is established as follows:

$$Npro_{it} = \beta_0 + \beta_1 Treat \times Post_{it} + \sum \beta_n ContVars_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (2)$$

In this equation, Treat represents whether a firm belongs to the treatment group, where the treatment group is coded 1 and the non-treatment group is coded 0. The value of Post is 1 in the year after the first use of technological convergence in digital and real industries in the processing group; otherwise, it takes a value of 0. Other variables were defined as consistent with the baseline regression.

This study also conducted a regression analysis using an alternative dependent variable. In the baseline regression, the index of the firm's new quality productive forces was used for the analysis. In the field of economics, productive forces and efficiency are often interchangeable, and total factor productivity (TFP) is commonly used as the dependent variable to measure the level of firm new quality productive forces (Wang and Du, 2025). Currently, the widely used methods for measuring total factor productivity include the Olley-Pakes (OP), Levinsohn-Petrin (LP), and the Ackerberg-Caves-Frazer (ACF) methods. Therefore, following the approach of Song *et al.* (2024), the LP method was employed to calculate total factor productivity.

Technological convergence in digital and real industries in firms is not only influenced by contemporaneous factors but also by various factors from past periods, including their own past values. Therefore, in this study, an explanatory variable (TechConv) was used to lag one and two periods to overcome the endogenous problems caused by the periodicity of technological convergence in digital and real industries.

Finally, heterogeneity tests were conducted to examine whether there were significant differences across regions and industries. Technological convergence in digital and real industries is part of an emerging sector that places a high demand on the development levels of both digital and physical economies within regions. Given the regional disparities in the development of technological convergence in digital and real industries across different areas, this study divides the experimental samples into three regions (East, Central, and West) and conducts regression tests separately. In terms of industry differences, the samples were categorized into four groups based on industry: manufacturing, non-manufacturing, high-tech, and non-high-tech. Based on the differences in product form, technology density, and market characteristics between the manufacturing industry and high-tech industries and other industries, the impact of technological convergence in digital and real industries on the new quality productive forces of enterprises in manufacturing, high-tech, and other industries may vary.

4. Results and Discussion

4.1 Descriptive Analysis

Table 2 presents the descriptive statistics for each variable. The dependent variable Npro has a mean of 5.55 and a standard deviation of 2.386. The Npro ranged from 1.586 to 15.220. These statistics indicate that the level of new quality productive forces of Chinese enterprises is low on average, whereas there are enterprises with higher levels. The explanatory variable TechConv has a mean of 0.416 with a standard deviation of 0.755, indicating that the data have higher variability.

Table 2: Summary statistics of variables

Variable	Mean	SD	Min	Max
Npro	5.550	2.386	1.586	15.220
TechConv	0.416	0.755	0	3.555
Size	22.690	1.269	20.400	26.110
Lev	0.424	0.185	0.084	0.828
ROE	0.080	0.091	-0.279	0.333
Cashflow	0.054	0.058	-0.097	0.219
Growth	0.144	0.252	-0.380	1.243
Loss	0.074	0.261	0	1
Board	2.141	0.190	1.609	2.639
Indep	37.480	5.314	33.330	57.140
Dual	0.245	0.430	0	1
TOP10	55.920	13.95	25.750	89.300
TobinQ	2.009	1.153	0.839	7.070
SOE	0.373	0.484	0	1
FirmAge	2.929	0.302	1.946	3.466
Big4	0.076	0.264	0	1

4.2 Baseline Regression Results

Table 3 presents the results of baseline regression. Columns (1) to (4) represent the stepwise regression results containing explanatory variables, control variables (ContVars), and fixed effects (Year FE and Enterprise FE). From Table 2, it is evident that the regression coefficients of the technological convergence in digital and real industries (TechConv) on enterprise new quality productive forces capacity (Npro) are consistently significant and positive. This indicates that enterprises engaging in more technological convergence activities in digital and real industries tend to have higher levels of new quality productive forces. In particular, the results in column (4) demonstrate that after adding some control variables and carrying out the year, the firm-fixed effect, the coefficient of the explanatory variable TechConv is 0.492, which is significant at the 1% level. This implies that for every 1% increase in the quantity of technological convergence in the digital and real industries, there is a corresponding increase of 0.492% in the enterprise's new quality productive force capacity. Thus, it can be concluded that technological convergence in digital and real industries significantly and positively influences the enhancement of enterprise new quality productive force capacity, which aligns with the theoretical analysis presented in this study. The integration of digital and physical technologies can elevate the quality of productive forces and transform industrial structures, thereby enhancing enterprise competitiveness and enabling high-quality economic development by optimizing processes, fostering innovation, and creating new business models (Liang and Tian, 2024).

Table 3: Baseline regression results

Variables	(1)	(2)	(3)	(4)
TechConv	0.365***	0.322***	0.507***	0.492***
	(7.37)	(6.36)	(9.75)	(9.79)
Size	-	0.298***	0.075*	0.044
		（6.87）	（1.7）	（1.04）
Lev	-	1.350***	0.844***	0.315
		（5.30）	（3.41）	（1.29）
ROE	-	3.270***	2.296***	1.682***
		（5.28）	（3.82）	(-2.90)
Cashflow	-	1.943***	1.389**	1.553**
		（2.74）	（2.03）	(2.33)
Growth	-	0.450***	0.472***	0.409***
		（2.92）	（3.13）	(2.82)
Loss	-	0.224	0.122	0.146
		（1.23）	（0.69）	(0.86)
Board	-	0.649***	1.119***	0.855***
		（2.66）	（4.74）	(3.76)
Indep	-	0.016*	0.022***	0.014*
		（1.87）	（2.74）	(1.89)
Dual	-	0.352***	0.357***	0.360***
		（3.93）	（4.15）	(4.34)
TOP10	-	0.025***	0.018***	0.018***
		（8.94）	（6.54）	(6.88)
TobinQ	-	0.271***	0.245***	0.204***
		（7.32）	（6.44）	(5.50)
SOE	-	0.402***	0.535***	0.476***
		（4.61）	（6.36）	(5.81)
FirmAge	-	0.661***	-0.342**	0.139
		（5.07）	（2.44）	(1.02)
Big4	-	0.334**	0.410***	0.476***
		（2.24）	（2.86）	(3.44)
Year FE	No	No	Yes	Yes
Enterprise FE	No	No	No	Yes
R^2	0.013	0.103	0.174	0.242

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; the t-values are shown in parentheses. The same applies to all of the tables.

4.3 Robustness Analyses

4.3.1 Instrumental Variable Approach

Historically, the penetration rate of fixed telephones has affected local internet penetration and development, which in turn correlates with the digital infrastructure support required for technological convergence in the digital and real industries of enterprises. Meanwhile, the impact of fixed telephones on total factor productivity has gradually diminished (Huang *et al.*, 2019). To address potential measurement issues arising from using single-year variables in fixed effects model tests, following Nunn and Qian (2014), we construct an interaction term between the average number of fixed telephones per ten thousand people at the city level in 1984 and Internet access at the city level as the instrumental variable for enterprise technological convergence in digital and real industries (denoted as FixTel). To some extent, the tool variable satisfied the requirements of correlation and exclusivity.

The results of the first and second stages are presented in Table 4 and columns (1) and (2), respectively. In the first stage, the coefficient of the instrumental variable (FixTel) on enterprise technological convergence in the digital and real industries (TechConv) is 0.000 and significant at the 1% level. This indicates a strong correlation between the instrumental variable (FixTel) and enterprise technological convergence in digital and real industries (TechConv). In the second stage, the coefficient of enterprise technological convergence in the digital and real industries on enterprise new quality productive forces is 5.3972, significant at the 1% level. This suggests that enterprise technological convergence in digital and real industries contributes significantly to the enhancement of new quality productive forces, consistent with the conclusions drawn earlier.

Table 4: 2SLS instrumental variable analysis

	(1) First stage	(2) Second stage
Variable	DV = TechConv	NPro
FixTel	0.0000*** （0.000）	
TechConv		5.3972*** （1.140）
Size	0.1642*** （0.013）	-0.7722*** （0.205）
Lev	0.0382 （0.077）	-0.4615 （0.453）
ROE	0.2982 （0.186）	-3.1178*** （1.131）
Cashflow	-0.7578*** (0.211）	5.2001*** （1.497）
Growth	-0.0681 （0.046）	0.7124** （0.280）
Loss	0.0820 （0.053）	-0.3052 （0.328）
Board	0.0513 （0.072）	0.5847 （0.424）
Indep	0.0010 （0.002）	0.0113 （0.014）
Dual	0.1445*** （0.026）	-1.1153*** （0.231）
TOP10	-0.0015* （0.001）	-0.0092* （0.005）
TobinQ	-0.0116 （0.012）	0.2624*** （0.069）
SOE	0.1707*** （0.026）	-0.3830 （0.248）
FirmAge	0.0492 （0.043）	-0.2746 （0.253）
Big4	0.2543*** （0.044）	-0.8270** （0.394）
Constant	-3.4288*** （0.340）	18.9542*** （4.328）
Industry / Year FE	Yes	Yes
Observations	3993	3993
R^2	0.245	

4.3.2 Propensity Score Matching (PSM) and Differences-in-Differences (DID) tests

The regression results of propensity score matching (PSM) is presented in Column (1) of Table 5, showing a statistically significant positive coefficient for technological convergence in digital and real industries at the 1% level, supporting the arguments of the baseline regression. In the PSM-DID approach, the propensity score of the whole sample in the mixed years is first matched, and the control variables are taken as the benchmark variables of enterprise characteristics. The sample group for the first use of technological convergence in the digital and real industries in the sample period is treated as 0. The 1-standard nearest-neighbour matching method of quasi-calipers was used to perform 1:1 no-put matching with the samples of the control group, and then DID estimation was performed according to equation (2). The results are shown in Column (2) of Table 5.

Considering that the matching results above may have the problems of inconsistent years of samples in the treatment group and the control group, and the unstable time series of samples in the control group, this study refers to Huang *et al.* (2023) and takes the year before the first use of technological convergence in the digital and real industries of enterprises in the treatment group as the benchmark. With the control group samples in the same year, 1:1 no-put-back proximity matching with standard calipers of 0.1 was performed to extract regression samples, so that the innovation behavior decision of enterprises in the treatment group was closer to the quasi-natural experiment setting. Column (3) of Table 5 presents the estimated results of DID after matching.

Table 5: Robustness checks- PSM and PSM-DID

Variables	(1)	(2)	(3)
TechConv	0.515*** (8.06)		
TreatxPost		0.595** (5.28)	0.615*** (7.64)
Size	-0.079 (-1.24)	0.014 (0.22)	0.094** (2.23)
Lev	-0.377 (-1.02)	-0.505 (-1.36)	-0.347 (-1.41)
ROE	-1.650* (-1.91)	-1.401 (-1.61)	-1.652*** (-2.78)
Cashflow	0.742 (0.74)	0.403 (0.40)	1.315* (1.96)
Growth	0.415* (1.90)	0.401* (1.82)	0.386*** (2.62)
Loss	0.329 (1.27)	0.411 (1.58)	0.187 (1.10)
Board	1.085*** (3.31)	1.218*** (3.68)	0.927*** (4.04)
Indep	0.017 (1.50)	0.018** (1.59)	0.015* (1.94)
Dual	-0.443** (-3.52)	-0.360*** (-2.84)	-0.325*** (-3.91)
TOP10	-0.016** (-4.18)	-0.018*** (-4.56)	-0.018*** (-6.92)
TobinQ	0.177*** (3.14)	0.170*** (2.99)	0.203*** (5.43)
SOE	0.460*** (3.75)	0.486*** (3.93)	0.477*** (5.76)
FirmAge	0.150 (0.75)	0.200 (0.99)	-0.108 (-0.79)
Big4	0.619*** (3.46)	0.702*** (3.90)	0.551*** (3.97)
Constant	4.121** (2.56)	1.713 (1.08)	1.142 (1.05)
Industry or Year FE	Yes	Yes	Yes
Observations	2064	2064	3993
R^2	0.263	0.250	0.235

Columns (2) and (3) show that the coefficient of the interaction term Treat×Post is significantly positive under the different matching methods. This indicates that firms' decision to engage in technological convergence in digital and real industries has a significantly positive impact on the enhancement of firm-level new quality productive forces, further corroborating the baseline conclusions of this study.

4.4 Regression Analysis with Alternative Dependent Variable and Lagged Variables

The regression results for the alternative dependent variables are listed in Table 6 (Model 1). The regression coefficient of technological convergence in the digital and real industries on the total factor productivity of enterprises is still positive, which verifies the robustness of the benchmark regression conclusion in this study. Columns (2) and (3) of Table 6 present the regression results with lagged variables, which the regression coefficients are both significantly positive. This indicates that technological convergence in digital and real industries in firms in the two preceding periods has a significant impact on new quality productive forces, thus confirming the findings of the baseline regression.

Table 6: Robustness checks – alternative dependent variable and lagged variables

Variables	(1) TFP_LP	(2) Npro	(3) Npro
TechConv	0.030*** (3.02)		
L1.TechConv		0.528*** (10.02)	
L2.TechConv			0.587*** (10.65)
Size	0.594*** (71.11)	0.021 (0.46)	-0.006 (-0.11)
Lev	0.636*** (13.27)	-0.389 (-1.46)	-0.501* (-1.73)
ROE	1.588*** (13.73)	-1.192* (-1.88)	-0.811 (-1.18)
Cashflow	0.282** (2.16)	1.244* (1.73)	0.785 (1.01)
Growth	0.091*** (3.18)	0.342** (2.15)	0.366** (2.13)
Loss	0.082** (2.48)	0.228 (1.28)	0.251 (1.32)
Board	-0.049 (-1.11)	0.828*** (3.37)	0.764*** (2.89)
Indep	-0.001 (-0.75)	0.015* (1.79)	0.014 (1.59)
Dual	-0.030* (-1.83)	-0.366*** (-4.07)	-0.392*** (-4.01)
TOP10	0.003*** (5.06)	-0.018*** (-6.28)	-0.018*** (-5.81)
TobinQ	0.020*** (2.77)	0.199*** (5.04)	0.210*** (4.99)
SOE	0.040** (2.50)	0.474*** (5.36)	0.475*** (5.00)
FirmAge	0.135*** (5.07)	-0.219 (-1.44)	-0.322* (-1.89)
Big4	-0.002 (-0.09)	0.477*** (3.20)	0.481*** (3.00)
Constant	-5.909*** (-27.70)	3.362*** (2.83)	5.870*** (4.50)
Industry or Year FE	Yes	Yes	Yes
Observations	3993	3590	3198
R^2	0.826	0.214	0.183

4.5 Heterogeneity in the Integration of Digital and Real Industries

4.5.1 Heterogeneity Test of Regional Differences in Firms

The experimental sample was divided into three regions (East, Central, and West), and regression tests were conducted separately. The results in Table 7 show that the promotion effect of technological convergence in digital and real industries on firms' new quality productive forces is significant in both the Eastern and Western regions, with coefficients of 0.435 and 0.637, respectively. However, this effect is not significant in the central region, indicating heterogeneity in the promotion effect of technological convergence in digital and real industries on new quality productive forces, consistent with the previous inference. The insignificant impact of technological convergence on firms' new quality productive forces in the central region may be attributed to multiple factors, including industrial structure, digital infrastructure, capital and talent constraints, the market environment, and firms' willingness for digital transformation. The Central region is primarily driven by traditional manufacturing industries, with a relatively lagging digital industry development and weaker technological absorption capacity. Additionally, insufficient digital infrastructure and policy support, along with limited access to funding and high-end talent, pose challenges to firms in the process of technological convergence. Furthermore, lower market competition reduces firms' motivation for digital transformation, further weakening the promotional effect of technological convergence. These findings suggest that efforts should focus on enhancing digital infrastructure, optimizing policy support, and improving firms' technological absorption capacity to facilitate the integration of digital technology with traditional industries.

Table 7: Results of heterogeneity test of regional difference in firms

Variables	(1) East	(2) Central	(3) West
TechConv	0.435*** (7.42)	0.056 （0.38）	0.637*** （5.66）
Size	0.271*** (5.56)	-0.338*** （-3.27）	-0.569*** （-3.99）
Lev	-0.902*** （-3.34）	-1.525** （-2.12）	3.228*** （4.55）
ROE	-1.075 （-1.59）	-2.397 （-1.55）	-3.827*** （-2.65）
Cashflow	0.326 （0.43）	3.872** （2.11）	4.628*** （2.82）
Growth	0.290* （1.73）	0.852** （2.53）	0.439 （1.33）
Loss	0.531*** （2.77）	-0.161 （-0.34）	-1.112*** （-2.75）
Board	0.543* （1.94）	3.598*** （5.92）	1.369*** （2.94）
Indep	0.026*** （2.7）	0.015 （0.87）	0.025 （1.50）
Dual	-0.417*** （-4.68）	-0.323 （-1.05）	0.163 （0.70）
TOP10	-0.024*** （-7.63）	-0.016** （-2.23）	-0.004 （-0.60）
TobinQ	0.281*** （6.83）	-0.404*** （-3.81）	0.337*** （3.17）
SOE	0.379*** （3.89）	0.238 （1.12）	0.868*** （3.82）
FirmAge	-0.211 （-1.40）	-0.309 （-0.62）	0.774** （2.17）
Big4	0.483*** （2.96）	0.313 （0.82）	-0.012 （-0.04）
Constant	-1.255 （-0.94）	6.989*** （2.93）	8.955*** （2.74）
Industry or Year FE	Yes	Yes	Yes
Observations	2887	536	570
R^2	0.294	0.489	0.279

4.5.2 Heterogeneity Test of Industry Differences in Firms

Manufacturing, as the pillar of China's real economy, holds a crucial position in technological convergence in digital and real industries. Within this convergence, the level of digital economic development in high-tech industries surpasses that of other sectors. As the samples were categorized into four groups–manufacturing, non-manufacturing, high-tech, and non-high-tech industries–the promotional effect of technological convergence in digital and real industries on firms' new quality productive forces across industries can be investigated. As shown in Table 8, the interaction term between technological convergence in digital and real industries (TechConv) and the manufacturing dummy variable (Mi) in Column (3) are significantly positive at the 5% level, indicating significant industry heterogeneity in the promotion effect of technological convergence in digital and real industries on firms' new quality productive forces. In Columns (1) and (2), the coefficients of the technological convergence in digital and real industries (TechConv) on New quality productive forces (Npro) are 0.371 and 1.098, respectively, suggesting a more significant promotion effect of the technological convergence in digital and real industries on non-manufacturing sectors. Similarly, in Column (6), the interaction term between technological convergence in digital and real industries (TechConv) and the high-tech industry dummy variable (Ti) is significantly positive at the 5% level, while the coefficients of technological convergence in digital and real industries (TechConv) on new quality productive forces (Npro) in Columns (4) and (5) are 0.391 and 0.758, respectively, indicating a more pronounced promotion effect of technological convergence in digital and real industries in non-high-tech sectors.

Table 8: Results of heterogeneity test of industry difference in firms

Variables	(1)	(2)	(3)	(4)	(5)	(6)
TechConv	0.371***	1.098***	0.506***	0.391***	0.758***	0.528***
	(7.64)	(5.79)	(10.09)	(7.00)	(6.74)	(10.4)
Mi			0.114**			
			(2.34)			
TechConv*Mi			0.182***			
			(5.59)			
Ti						0.093*
						(1.92)
TechConv*Ti						-0.578***
						(-4.50)
Size	0.016	0.067	0.06	0.138***	-0.203***	0.044
	(0.38)	(0.40)	(1.41)	(2.75)	(-2.68)	(1.04)
Lev	0.228	-4.120***	-0.348	-0.427	0.300	-0.221
	(0.96)	(-4.46)	(-1.42)	(-1.53)	(0.58)	(-0.90)
ROE	-2.427***	3.659*	-1.908***	-1.396**	-0.847	-1.660***
	(-4.21)	(1.67)	(-3.24)	(-2.11)	(-0.72)	(-2.81)
Cashflow	1.188*	5.290**	1.479**	0.696	6.779***	1.440**
	(1.84)	(2.10)	(2.22)	(0.89)	(5.77)	(2.15)
Growth	0.529***	-0.536	0.395***	0.239	0.718**	0.390***
	(3.64)	(-1.15)	(2.70)	(1.45)	(2.45)	(2.66)
Loss	-0.005	1.435**	0.114	0.24	0.246	0.162
	(-0.03)	(2.27)	(0.67)	(1.24)	(0.77)	(0.96)
Board	0.775***	1.464*	0.810***	0.529**	1.669***	0.928***
	(3.47)	(1.77)	(3.56)	(2.03)	(3.77)	(4.07)
Indep	0.017**	-0.021	0.014*	0.018**	0.022	0.017**
	(2.40)	(-0.62)	(1.84)	(2.06)	(1.52)	(2.18)
Dual	-0.319***	-0.784**	-0.362***	-0.473***	0.074	-0.364***
	(-4.00)	(-2.37)	(-4.38)	(-5.12)	(0.41)	(-4.39)
TOP10	-0.022***	-0.012	-0.018***	-0.021***	-0.004	-0.018***
	(-8.61)	(-1.17)	(-6.89)	(-6.94)	(-0.78)	(-6.82)
TobinQ	0.212***	0.253*	0.205***	0.317***	-0.406***	0.210***
	(5.88)	(1.83)	(5.55)	(7.65)	(-4.99)	(5.67)
SOE	0.267***	1.938***	0.448***	0.453***	0.673***	0.450***
	(3.38)	(5.86)	(5.46)	(4.79)	(4.35)	(5.47)
FirmAge	-0.205	0.903*	-0.131	-0.172	0.133	-0.111
	(-1.54)	(1.80)	(-0.96)	(-1.12)	(0.47)	(-0.81)
Big4	0.689***	-0.202	0.516***	0.555***	-0.046	0.495***
	(5.22)	(-0.31)	(3.74)	(3.43)	(-0.17)	(3.58)
Constant	2.582**	-2.13	2.211**	0.116	4.765**	1.908*
	(2.54)	(-0.50)	(2.02)	(0.09)	(2.39)	(1.73)
Industry or Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3414	579	3993	3143	850	3993
R^2	0.176	0.467	0.248	0.225	0.442	0.246

Notes: Models (1) and (2) consist of manufacturing and nonmanufacturing industries, respectively. Model (3) has a dummy variable for the manufacturing industry (Mi) and an interaction term of TechConvxMi. Models (4) and (5) include high-tech and non-high-tech industries, respectively. Model (6) has a dummy variable for the high-tech industry (Ti) and an interaction term of TechConvxTi.

5. Conclusion

China’s economy has shifted to high-quality development. The deep integration of the digital economy and the real economy is an important strategic measure to promote the optimization of China's economic structure and the transformation of growth drivers. Technological convergence in digital and real industries is a key focus for achieving the deep integration of digital and real economies. It is an indispensable driving force for enhancing the level of new quality productive forces in enterprises, achieving digital transformation and promoting high-quality development. This study, based on financial statement data and patent information of Chinese listed companies from 2013 to 2022, examines the impact and mechanism of technological convergence in digital and real industries on enterprises' new quality productive forces. The empirical results show that technological convergence in digital and real industries helps enterprises innovate in productivity skills and improve quality, thereby forming new quality productive forces. A heterogeneity analysis of enterprises in different regions and industries shows that the promoting effect of new quality productive forces is more significant for enterprises in the eastern and western regions, non-manufacturing industries, and non-high-tech industries.

Based on the research conclusions, this study provides the following insights. First, China needs to improve its data element market system and accelerate the cultivation of new quality productive forces. Second, accelerating the construction of a digital talent team is the basic condition and core content for forming new quality productive forces. Therefore, it is necessary to strengthen discipline construction in the fields of digital economy and artificial intelligence, improve the top-level design for discipline adjustment and optimization, and organically combine digital economy and artificial intelligence research with talent cultivation. Third, digital infrastructure forms the backbone of the digital economy, enabling innovation, application, and development of new productive forces. The Chinese government must invest in and optimize this infrastructure to ensure comprehensive coverage, high speed, low latency, and intelligence, including advancements in 5G networks, data centres, AI platforms, and cloud computing, while enhancing network security, data resource sharing, and the impact of AI technology.

This study has some limitations. First, owing to the heterogeneity of digital technology and differences in the maturity of physical industry technology, the degree of modularity of technology, and the characteristics of related products, technological convergence may exhibit heterogeneity in speed, intensity, and economic effects. Second, future research could combine other data and methods to study the impact and mechanisms of technological convergence on other dimensions of high-quality enterprise development. There are still many perspectives worth exploring regarding the micro-mechanisms of technological convergence in digital and real industries.

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