

Technology Convergence of Digital and Real Industries and Corporate Financial Mismatch: A Study Based on Chinese Listed Companies

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Abstract. In order to explore the changes in the degree of corporate financial resource mismatch in the process of the rising level of technology convergence of digital and real industries, this paper empirically examines the impact of technology convergence of digital and real industries on corporate financial resource mismatch by utilizing the panel data of A-share non-financial listed companies in Shanghai and Shenzhen from 2011-2023 on the basis of theoretical analysis. The findings show that the enhanced level of technology integration of digital and real industries significantly suppresses the risk of corporate financial resource mismatch, and this conclusion still holds after a series of robustness tests. The above impact is mainly realized through the mechanism of alleviating the degree of corporate financing constraints and enhancing corporate knowledge width.

Keywords: Technology convergence of digital and real industries; Knowledge width; Financial mismatch.

1. Introduction

In the new development stage of a new round of scientific and technological revolution and accelerated industrial change, the deep integration of the digital economy with the real economy has become a necessary path for China to realize high-quality economic development. Promoting the integration of the digital economy with the real economy is a major decision made for Chinese-style modernization, and an important initiative for China to move towards the road of high-quality development and win a new round of international competition. According to the Research Report on the Development of China's Digital Economy (2023) released by the China Academy of Information and Communication Technology, China's digital economy will reach 50.2 trillion yuan in 2022, ranking second in the world. Inter-industry technological convergence is a prerequisite for industrial convergence to occur and the most important driving factor for industrial convergence (Han and Sohn, 2016). In recent years, emerging digital technologies such as artificial intelligence, big data, cloud computing, blockchain, and the Internet of Things (IoT) have become increasingly integrated with traditional industries (Xin et al., 2023; Sun et al., 2024; Liu et al., 2024), enhancing knowledge exchange and product competitiveness within and between firms. Enterprises realize the integration of digital economy industry and real economy industry at the technological level (hereafter referred to as technology convergence of digital and real industries) by applying digital economy industry technology to the technological innovation process as well as digitally transforming the technology of real economy industry (Huang and Gao, 2023).

A comprehensive body of literature exists regarding the causes and consequences of financial

resource misalignment within enterprises. In the context of China, the government-directed financial system is susceptible to polarization in the distribution of financial resources, which contributes to the widespread occurrence of financial mismatches among enterprises. The notion of corporate financial resource mismatch is derived from the theory of financial asset allocation. It pertains to the discrepancy between the actual efficiency of financial resource allocation and the optimal efficiency that should be achieved by enterprises in their allocation of financial resources (Liu et al., 2022). It has been shown that the degree of financial mismatch significantly affects factors such as corporate financing cost (Li et al., 2023), default risk (Liu and Nie, 2022), debt financing capacity (Feng and Liang, 2022), and total factor productivity (Li et al., 2021). Current research indicates that various mechanisms, including digital transformation (Ding et al., 2024), securities regulations (Li et al., 2025), and digital finance (Yin and Wang, 2024), are effective in addressing the discrepancies in firms' financial resources. However, few current articles have examined the relationship between the technology convergence of digital and real industries and the mismatch of financial resources in firms. The study presented in this paper contributes to the expansion of the research framework concerning the integration of the digital economy with the real economy, while also proactively investigating viable strategies to address the misalignment of corporate financial resources.

2. Theoretical analysis and research hypotheses

The limitations of traditional physical industry technologies, which were previously constrained by substantial data requirements and complex data processing challenges, have been alleviated through advancements in digital technology. As the real industry sector continues to be explored and expanded, the diverse application scenarios and the increasing scale of these applications have necessitated ongoing updates and iterations of digital technology. Current research indicates that digital technology can effectively integrate both internal and external information through the utilization of big data, cloud computing, and other related technologies. This integration offers more comprehensive and precise data support for the real economy, thereby enhancing the capacity for the integration of financial resources within enterprises. Accordingly, hypothesis H1 is proposed

H1: An increase in the level of technology convergence of digital and real industries can significantly reduce the mismatch of financial resources faced by firms.

Technology convergence in the digital and real industries can promote enterprise knowledge width (Huang and Gao, 2023). The embedding of digital industrial technology into real industrial technology has weakened enterprise boundaries in the process of technological innovation, accelerated the flow of encodable knowledge contained in technology in the form of data among innovation subjects, and reduced the constraints on the spillover effect of real industrial technology imposed by factors such as regional division, flow carriers and geopolitics (Wu et al., 2019). As the breadth of knowledge in a company increases, its competitive capacity within the industry is strengthened. Concurrently, the utilization of digital technology improves the capabilities of organizations in terms of information collection and integration, thereby significantly enhancing their ability to allocate financial resources effectively (Ding et al., 2024).

Additionally, when the integration of digital technology within the real industries is low, the organization's capacity to gather and organize information is significantly diminished. This limitation hampers the enterprise's ability to effectively respond to the rapidly evolving product demands in the market, resulting in diminished competitiveness relative to peers in the same

industry. Consequently, the enterprise faces heightened financing constraints (Ding et al., 2024). Accordingly, hypothesis H2 is proposed.

H2: The increase in the level of technology convergence of digital and real industries leads to a decrease in the degree of financial resource mismatch by enhancing the knowledge width of firms and reducing the channels of corporate financing constraints.

3. Research design

3.1. Model construction

In order to explore the impact of technology convergence in the digital and real industries on the mismatch of firms' financial resources, the following model has been set up.

$$FM_{i,t} = \alpha_0 + \alpha_1 TechConv_{i,t} + \sum Controls_{i,t} + Year_t + Firm_i + \varepsilon_{i,t} \quad (1)$$

Where *TechConv* is the level of technology integration in the digital and real industries, *FM* represents the degree of financial mismatch. The subscripts *i* and *t* in the formula represent the enterprise and the year, respectively. In the empirical analysis, *Year* and *Firm* respectively represent the firm fixed effect and time fixed effect. At the same time, $\varepsilon_{i,t}$ represents the random error term. This paper also adopts cluster-robust standard errors, clustering the standard errors at the firm level.

3.2. Variable measurement

Referring to Huang and Gao (2023), this paper captures the flow characteristics of digital industry knowledge in the technological innovation of real industry based on patent citation information, in order to measure the digital-real industry technology integration behavior of enterprises.

In addressing the issue of corporate financial resource misallocation, this paper adopts the research methodology established by Ding et al. (2024), utilizing the corporate interest rate as an indicator of the extent of resource misallocation within firms. This approach is grounded in the principles of general equilibrium theory. When a firm's financial resources are misallocated, there will be a discernible deviation from the firm's interest rate in a state of equilibrium. A higher numerical value indicates a greater degree of misalignment, while a lower value signifies a lesser degree of misalignment. The specific formula for measurement is presented as follows. Where fm_{ijt} denotes the corporate interest rate, and fm_{jt} denotes the average level of the industry in which the firm operates.

$$FM = \frac{|fm_{ijt} - fm_{jt}|}{fm_{jt}} \quad (2)$$

Referring to the articles of Ding et al. (2024) and Li et al. (2023), this paper sets a series of control variables as shown in Table 1.

3.3. Sample selection and data sources

The data of A-share companies listed in Shanghai and Shenzhen from 2011 to 2023 are selected as the research sample for this study. Financial data and corporate governance data are from the CSMAR database, while other macro-level data are from the China Statistical Yearbook and the authors' calculations. In this paper, after excluding ST companies and companies with incomplete information, all continuous variables are truncated at 1% and 99% levels to control the effect of outliers on the estimation results. Finally, a total of 15,946 study samples are obtained. The

descriptive statistics of each variable are shown in Table 1.

Table 1. Descriptive statistical analysis

Property of variable	Variable	N	Mean	SD	Min	Max
Explained variable	FM	15,946	0.547	0.42	0	8.768
Explanatory variable	TechConv	15,946	1.415	1.281	0	6.603
Control variable	Rgr	15,946	0.004	0.049	-0.036	4.346
	Ito	15,946	1.747	100.214	0	8722.46
	Cato	15,946	0.012	0.009	0	0.121
	Lev	15,946	0.005	0.002	0	0.016
	age	15,946	2.303	0.666	0.693	3.526
	Pat	15,946	3.57	1.284	0	8.905
	Liq	15,946	0.047	0.064	-0.42	0.839
	BS	15,946	2.124	0.198	1.386	2.89
	EDF	15,946	0.002	0.032	0	1
	Size	15,946	22.57	1.32	18.611	28.697
	Intfp	15,946	8.719	1.02	5.55	12.977
Gov	15,946	7.478	0.301	6.972	9.532	

4. Empirical results and analyses

4.1 Baseline regression results

To test H1, this paper first empirically tests equation (1), and the test results are shown in Table 2. First, the impact of technology convergence of digital and real industries and the mismatch of corporate financial resources is tested without controlling for fixed effects, and the test results are shown in column (1). Second, regression is conducted after controlling enterprise fixed effects and year fixed effects, and the regression results are shown in column (2). In addition, on the basis of controlling the fixed effects, all control variables are included in the analytical framework for regression, and the results are shown in column (3). The results of all three regressions above show that the increase in the level of technology convergence of digital and real industries significantly leads to a decrease in the degree of mismatch of financial resources in enterprises, and the regression results hold at the 1% level of significance. In summary, H1 is verified.

Table 2. Results of basic regression analysis

Variables	(1)	(2)	(3)
	<i>FM</i>		
<i>TechConv</i>	-0.0253*** (0.0025)	-0.0270*** (0.0050)	-0.0202*** (0.0057)
<i>Rgr</i>			0.0518 (0.0676)
<i>Ito</i>			-0.0002** (0.0001)
<i>Cato</i>			-0.4592 (0.8706)

<i>Lev</i>			1.9518
			(5.6172)
<i>age</i>			0.0952***
			(0.0301)
<i>Patent</i>			0.0047
			(0.0057)
<i>Liq</i>			0.4409***
			(0.0737)
<i>BS</i>			-0.0534
			(0.0413)
<i>EDF</i>			0.1708***
			(0.0615)
<i>Size</i>			-0.0518***
			(0.0194)

(Continued Table)

Variables	(1)	(2)	(3)
	<i>FM</i>		
<i>Intfp</i>			-0.0496**
			(0.0196)
<i>Gov</i>			0.0181
			(0.0552)
<i>Constant</i>	0.5831***	0.5837***	1.8945***
	(0.0048)	(0.0071)	(0.5408)
<i>Year FE</i>	No	Yes	Yes
<i>Enterprise FE</i>	No	Yes	Yes
<i>N</i>	15,946	15,946	15,946
<i>R-squared</i>	0.0059	0.4507	0.4575

4.2 Endogenous

Some unobservable factors at the firm level may lead to reverse causality problems, resulting in endogeneity in the regressions. To mitigate the endogeneity problem, this paper constructs an instrumental variable based on the mean values of other firms with the same innovation capability in the same year. Specifically, firms are categorized by the number of patent applications, grouped by deciles, and the weighted mean of the explanatory variable (*TechConv*) of other firms in the same group is calculated as the instrumental variable (denoted as *Avg_TechConv*). The aggregation by grouping can effectively mitigate the influence of reverse causality due to the internal characteristics of the firms, and the mean values of the explanatory variables of other firms can map individual differences and guarantee the exclusivity of the instrumental variables. Moreover, the calculation based on the grouping of firms' innovation capabilities can effectively exclude the potential impact of firm characteristics on the benchmark regression conclusions after controlling for firm fixed effects. In summary, the instrumental variable better meets the requirements of relevance and exclusivity.

In this paper, two-stage least squares (2SLS) is used for instrumental variables regression, and

the regression results of the first stage and the second stage are shown in columns (1) and (2) of Table 3, respectively. The p-value of the LM statistic and the Wald F-statistic in Table 3 indicate that the instrumental variables selected in this paper are highly rational. The regression result in column (1) shows that the coefficient of influence of instrumental variables on explanatory variables is significantly positive at 1% level, which satisfies the correlation requirement for instrumental variable selection. Column (2) shows that the regression coefficient of the explanatory variable (*TechConv*) is still negative, and the significance has decreased but is still significant at the 5% level, indicating that the baseline conclusion of this paper is more robust.

Table 3. Endogeneity test

Variables	(1)	(2)
	<i>TechConv</i>	<i>FM</i>
<i>Avg_TechConv</i>	0.7439***	
	(0.0165)	
<i>TechConv</i>		-0.0230**
		(0.0111)
<i>Kleibergen-Paap rk LM statistic</i>	753.839*** (<i>P</i> =0.0000)	
<i>Wald F statistic</i>	2024.543	
<i>Controls</i>	Yes	Yes
<i>Year FE</i>	Yes	Yes
<i>Enterprise FE</i>	Yes	Yes
<i>N</i>	15,946	15,946

4.3 Robustness tests

Given the intricate nature of the mechanisms through which the integration of digital and traditional industrial technologies influences the misalignment of corporate financial resources, it is plausible that such effects may exhibit a temporal lag. Consequently, this study employs the lagged one-period value of digital and real industry technology convergence (*L_TechConv*) as a substitute for the contemporaneous value of the explanatory variable (*TechConv*) in Equation (1) for re-estimation, with the regression outcomes presented in column (1) of Table 4.

Furthermore, recognizing that the mismatch of corporate financial resources may be influenced by its own previous values, this research incorporates the lagged one-period value of corporate financial resource mismatch into Equation (1) as a control variable and subsequently re-estimates the equation, with the results displayed in column (2) of Table 4.

To mitigate the potential influence of fixed effects selection on corporate financial resource allocation, this study substitutes corporate fixed effects with industry fixed effects in Equation (1) and conducts a re-estimation, with the results provided in column (2) of Table 4.

The findings indicate that the three robustness checks outlined above do not alter the significance or direction of the benchmark regression results, thereby reinforcing the robustness of the conclusions drawn in this paper.

Table 4. Results of robustness test

Variables	FM		
	(1)	(2)	(3)
	Controlling for lags in the effects of explanatory variables	Consider the effect of the explanatory variables themselves	Industry fixed effect
<i>L_TechConv</i>	-0.0195***		
	(0.0058)		

(Continued Table)

Variables	FM		
	(1)	(2)	(3)
	Controlling for lags in the effects of explanatory variables	Consider the effect of the explanatory variables themselves	Industry fixed effect
<i>TechConv</i>		-0.0175***	-0.0316***
		(0.0062)	(0.0046)
<i>L_FM</i>		2.3754***	
		(0.7267)	
<i>Constant</i>	2.3754***	1.7908***	1.7001***
	(0.7267)	(0.6758)	(0.1653)
<i>Controls</i>	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes
<i>Enterprise FE</i>	Yes	Yes	No
<i>Industry FE</i>	No	No	Yes
<i>Observations</i>	10,514	10,514	15,946
<i>R-squared</i>	0.5203	0.5444	0.0746

4.4 Mechanism analysis

In order to test the mediating mechanism of H2, this paper first tests the inhibitory effect of technology convergence on financing constraints in digital and real industries. Second, the financing constraint variable is included in the benchmark regression equation to verify the significance and direction of the technological convergence of digital and real industries variable affecting the mismatch of corporate financial resources at this time. This paper uses the *KZ* index to measure the degree of financing constraints of enterprises, and the regression results are shown in columns (1) and (2) of Table 5. The impact mechanism of technological convergence of digital and real industries on the financial mismatches of enterprises is achieved through alleviating financing constraints. In summary, H2 is proved.

In order to test the mediating mechanism of H2, this paper first tests the role of technological integration of digital and real industries on the growth of corporate knowledge width. Second, the knowledge width variable is included in the benchmark regression equation to verify the significance and direction of the digital and real industry technology integration variable affecting the financial resource mismatch of enterprises at this time. The regression results are shown in

columns (3) and (4) of Table 5. Referring to Huang and Gao (2023), this paper calculates the firm's knowledge width in order to measure the complexity of the knowledge contained in the firm's technological innovation. The impact mechanism of technological convergence of digital and real industries on the financial mismatches of enterprises is achieved through promoting the rise in the level of corporate knowledge width. In summary, H2 is proved.

Table 5. Regression analysis of intermediary effects.

Variables	(1)	(2)	(3)	(4)
	<i>KZ</i>	<i>FM</i>	<i>KnowWidth</i>	<i>FM</i>
<i>TechConv</i>	-0.0216*	-0.0198***	0.0024*	-0.0199***
	(0.0114)	(0.0057)	(0.0013)	(0.0057)
<i>KZ</i>		0.0164***		
		(0.0053)		
<i>KnowWidth</i>				-0.1116*
				(0.0676)
<i>Constant</i>	8.1148***	1.7612***	0.6141***	1.9630***
	(1.1337)	(0.5447)	(0.0980)	(0.5410)
<i>Controls</i>	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes
<i>Enterprise FE</i>	Yes	Yes	Yes	Yes
<i>Observations</i>	15,946	15,946	15,946	15,946
<i>R-squared</i>	0.8950	0.4580	0.5493	0.4577

5. Summary

This study aims to investigate the alterations in the extent of corporate financial resource mismatch as a result of the increasing technological integration within digital and real industries. To achieve this, the research empirically analyzes the influence of technological integration on corporate financial resource mismatch, utilizing panel data from A-share non-financial listed companies in Shanghai and Shenzhen spanning the years 2011 to 2023, grounded in theoretical analysis. The results indicate that a heightened level of technology integration in digital and real industries significantly mitigates the risk of corporate financial resource mismatch. This conclusion remains robust even after conducting various robustness tests. Based on these conclusions, the paper makes the following recommendations:

It is necessary to focus on the integration and application of digital industrial technology in the innovation process and innovation results of the real economy industrial technology, and to utilize artificial intelligence and other digital technologies to reduce costs and increase efficiency for the process of updating and iterating the real industrial technology. In the development process, special attention should be paid to the digital technological innovation landing in the empowerment of the development of the real economy, and to the integration of technology as the driving force of incremental innovation.

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