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Impact of Digital Finance on Manufacturing Technology Innovation: Fixed-Effects and Panel-Threshold Approaches

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Abstract: Digital finance (DF) has provided important financial support for the transformation and upgrading of China's manufacturing industry. Innovation is the engine of industrial upgrading. To solve the dilemma of developing the manufacturing industry, it is necessary to enhance independent innovation capabilities. On this basis, this article studies the impact of DF on manufacturing technology innovation (MTI). It uses the data of listed manufacturing firms in the Shenzhen and Shanghai A-share markets from 2011 to 2020 to establish a fixed-effects model and a panel-threshold model for empirical analysis. The results revealed that, first, DF significantly accelerates technological innovation in manufacturing enterprises and has a significant positive impact on technological innovation. Secondly, DF drives manufacturing enterprises' technological innovation by alleviating financial constraints (FCs). Thirdly, there is a dual-threshold effect based on market competition between DF and MTI based on market competition, and the promotion effect of DF on technology innovation decreases with the increasing degree of market competition. Finally, DF better enhances the technological innovation of non-state-owned manufacturing firms in the respective regions compared to state-owned firms. In terms of factor-intensive types, DF is more able to advance the innovative technologies of labor-intensive and capital-intensive enterprises, while it has no significant positive effect on technology-intensive enterprises. Policy implications are suggested to boost manufacturing technology innovation and aid future studies.

Keywords: digital finance; manufacturing technology innovation; mechanism analysis

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1. Introduction

Digital transformation and technology advancement have expanded R&D activities and product enhancements across numerous manufacturing businesses [1,2]. Since the reform and opening up, China's manufacturing industry has formed an independent and complete modern industrial system driven by cost advantages and has maintained the world's largest scale and total quantity for many consecutive years. Nowadays, due to technological backwardness, weakened labor advantages, and insufficient soft power, the manufacturing industry in China faces the dilemma of being "big but not strong". As a result, the country must shift from developing a "high-speed-based" to a "high-quality-based" manufacturing industry. At present, the new round of technological revolution has had a profound impact on global technology and market allocation, leading to significant changes in manufacturing processes and business models. Faced with the complex global situation, countries such as the United States, Britain, and Germany are accelerating the layout of manufacturing technology innovation (MTI). Currently, China has established 24 national-level manufacturing innovation centers, 187 ministerial key laboratories, and 125 industrial technology basic public service platforms. These establishments provide conditions and opportunities for promoting the marketization of innovation achievements and achieving the precise matching of supply and demand. They also help provide a good ecological environment for manufacturing and industrial development. Technological innovation is an important engine for enhancing the manufacturing industry's core competitiveness. It is also an imperative influencer for promoting highly rated economic development.

The real economy's development cannot do without financial vitality. An effective supply of finance is a key factor in catalyzing the innovation of the manufacturing industry. Traditional finance has structural imbalances and domain mismatches in serving the real economy [3]. This has created an insufficiency in meeting manufacturing innovation needs. With the penetration and application of digital technologies in the financial field, a new financial format with inclusive characteristics has emerged, which is digital finance (DF). DF can bridge the blind spots of traditional financial services, reduce service costs and entry barriers, improve financing efficiency, and effectively support the real economy's development. The key to solving the manufacturing industry's problems is to integrate DF into the process of MTI. The problems include the double pressure of technological pushback from developed countries and the lack of core technologies in the manufacturing industry. Studies regarding DF in various industries have been conducted, as is discussed in the Section 2 of this study. However, a dearth of research in the manufacturing sector needs to be addressed. New evidence that considers technological innovativeness as far as DF is concerned is imperative. In that sense, the novelty of this paper is twofold. First, this study is among the earliest, if not the first, to investigate the impact of digital finance on manufacturing innovation technology in China. This is important because of the intensive development and contribution of the manufacturing sector in China and the world at large. Second, the paper uses the fixed-effect and panel-threshold approaches, which have not been utilized yet in this kind of research, to aid its investigation.

Under these considerations, this paper intends to answer the following questions in general: (1) Can DF truly promote the manufacturing enterprises' technological innovation? (2) What is the mechanism of action? (3) Do market structure factors affect DF's effectiveness? (4) Is there heterogeneity in the impact of DF, given the differences in regions and the nature of enterprises? By answering these questions through empirical analysis, the following contributions will be made. First, the study will lay a strong foundation for future studies regarding manufacturing innovation technology. This topic is grounding its roots in China and extending to other parts of the world to boost the manufacturing industry. As a result, a basis will be drawn from this study's findings to develop other models that will enhance the area. Moreover, the manufacturing industry worldwide is known to be very dependent on traditional financing and operation, which is detrimental to growth and operations. The benefits of digital finance in promoting the manufacturing industry's innovativeness in the technological and digitalized world are key. In that case, evidence from this study will assist them in transitioning to the new era of digital innovation technology. Finally, the policy implications outlined in this study will help decision-makers, policymakers, and other stakeholders to formulate policies to guide manufacturing companies into being innovative. They will be exposed to the need to invest and embrace digital finance in the manufacturing sector.

The remainder of the study is structured as follows. In Section 2, the study discusses the relevant literature. Section 3 outlines the theoretical analysis and hypotheses. Section 4 presents the research design and methodology. Section 5 presents the empirical analysis, and Section 6 concludes the study with suggested policy implications.

2. Literature Review

2.1. Digital Finance

Digital finance refers to the use of digital technology by financial institutions and Internet corporations to develop related businesses like capital finance, payments, and information intermediation; hence, a new technological model that extends beyond conventional financial operations is established [4,5]. It is also known for providing conventional financial services digitally via computers, tablets, and smartphones. This phrase has also been used to refer to how new technology has affected the financial services sector. The old method of providing banking and financial services has been revolutionized by several new products, applications, processes, and business models. Digital finance can open up access to financial services for underprivileged communities in places without the necessary physical infrastructure (https://finance.ec.europa.eu/digital-finance/what-digital-finance_en, accessed on 10 July 2023). In the manufacturing sector, which is the focus of this study, digital finance can enhance the sector through technological innovativeness to boost production and meet consumer needs. There is a lot of relevant literature about DF, and some studies have been discussed. At the macro level, it includes economic growth, traditional finance, and industrial structure. Georgiana et al. [6] used data from Central and Eastern European countries and concluded that DF enhances the accessibility of financial services and thus stimulates economic growth. The study highlighted the impact of DF in elevating and strengthening the financial sector of a country. In similar studies that intended to establish the impact of DF and its association with the urban–rural income gap, it was revealed that DF accelerates the reduction of the urban–rural income gap [7] and promotes residents' consumption [8]. Helen et al. [9] investigated the effect of digitization on traditional finance and found that financing sources based on DF have increased. The study highlighted the role DF has come to play as a substitute and complement to traditional finance in boosting industries. In an investigation into the industrial structure of firms, Ren et al. [10] found that DF advances industrial structure upgrades, with consumption, entrepreneurship, and innovation playing important intermediary roles. The study revealed that, at the micro level, not only are these factors included, but financing, total factor productivity, and corporate innovation are also key. To solve the problems of poverty and unemployment, Fatturroyhan [11] proposed a financial technology platform that can directly provide funds for small- and medium-sized enterprises (SMEs), thus helping to alleviate poverty and unemployment. It was opined in the study that this technology is a great step towards the realization of sustainable goals and eradicating some of the major problems countries face. Some scholars have argued about the real impact of DF on SMEs, and a study by Rahayu et al. [12] proved that DF helps SMEs to overcome financing problems. It has the capacity to give them opportunities to compete with bigger corporations, given specific conditions. DF was also found to help enhance the total factor productivity of entities such as enterprises and banks [13,14]. When banks rely on DF, it improves their customers' fund security and enhances their trust in them. In addition to these findings, scholars that studied DF have provided evidence that DF promotes corporate innovation [15,16]. Its relevance to the corporate world is incomparable to the traditional one. With DF, most corporations have grown beyond imagination and achieved their set targets. In a similar study related to the current study, Han et al. [17] proved that DF could improve the innovation performance of high-tech manufacturing enterprises. This gives enough evidence that DF has been a great topic of discussion in uplifting the face of industries in various sectors.

2.2. Manufacturing Technology Innovation

Scholars have studied the factors influencing technology innovation in manufacturing firms from different perspectives. This discussion has laid a strong foundation for emerging studies and has been relevant to the technological development of manufacturing industries. For instance, Li et al. [18] concluded that environmental regulations inhibit the efficiency of technological innovation in manufacturing enterprises. In their opinion, these environmental laws generally regulate the entire industry and do not consider the specifics of every entity, leading to a negative impact on these manufacturing enterprises. Hanifah et al. [19] studied the impact of government support and innovation culture on corporate innovation based on the manufacturing of SMEs in Malaysia. In their research, support from the government and developing an innovative culture had a great potential to enhance corporate innovation in the manufacturing sector. Taking a shred of comparative evidence from the United States and China, Chakravorty et al. [20] found that China's import competition positively impacts US manufacturing innovation. This can be attributed to the immense development of China's technological innovations reaching its borders to attract other nations. In a more specific space, Charles et al. [21] examined the relationship between governmental policy on manufacturing technological innovation and proved that government institutional and policy support positively impact the innovation capabilities of manufacturing SMEs. In other words, crucial policies can drive manufacturing companies toward technological innovation. In a much-narrowed space, some scholars have studied this subject from an internal factors perspective. A typical example is the study of Sabourin et al. [22], which explored the determinants of innovation activities of Canada's manufacturing industry from the perspectives of intellectual property rights and scale. The empirical findings of the study revealed that technological innovations have enhanced the property rights and scale of these manufacturing firms in Canada. From this same perspective in Thailand, Phakpoom et al. [23] found that the breadth of knowledge sources and management capabilities could significantly improve the enterprises' innovation performance based on Thai manufacturing enterprise data. In addition to these developments, scholars have established that MTI impacts the development of industry and businesses. To mention a few, Xie et al. [24] found that technological, product, and institutional innovations have a significant positive driving effect on manufacturing upgrading, and this effect is more significant in technological innovation. Again, Kafetzopoulos et al. [25] found that the innovation capability of manufacturing businesses directly affects product quality and operational performance. Moreover, it indirectly affects financial performance. Finally, a study by Younas et al. [26] also concluded that technological innovation positively affects the performance of the manufacturing industry in Pakistan.

2.3. Digital Finance and Manufacturing Technology Innovation

There is limited direct research investigating the impact of DF on MTI in the existing literature. This has created a need for this study in the body of literature. However, the few that relate to this subject have been discussed. In a study conducted by Li et al. [27], it was concluded that a digitized economy could facilitate the digital transformation of manufacturing enterprises, which in turn drives them to engage in technological innovation. Again, a study by Chen et al. [28] that sought to investigate the effect of DF on manufacturing firms' servitization confirmed that DF helps the development of manufacturing servitization, where innovation plays a mediating role. Moreover, the studies of Zhang and Tian et al. [29,30] placed DF and the sustainable innovation performance of manufacturing firms under investigation and found that DF enhances the performance and sustainable innovation performance of manufacturing enterprises. Another study by Santiago et al. [31] that investigated if digital infrastructure has impacted the technological innovation of manufacturing firms proved that digital infrastructure construction could promote technological innovation in manufacturing enterprises. Last but not least, Jiang et al. [32] further confirmed in their study that the diffusion of 5G technology significantly improves the efficiency of technological innovation in manufacturing enterprises.

In reviewing the literature on DF by domestic and foreign scholars, there has been sufficient research on the connotation, development, and impact of DF, including various aspects of economic growth, consumption, industrial structure, enterprise innovation, and total factor productivity. Not only has there been limited research, but there are also limited methodological approaches for studying such a prominent sector in China and the world at large. Research on manufacturing technological innovation is also relatively rich and has gained popularity in the last decade. It is developing gradually with external influencing factors like environmental regulations, policy systems, government support, and internal factors, including intellectual property rights and management capabilities. While most studies on the interplay between DF and innovation have focused on the regional, city, or firm level, fewer studies have been conducted directly on the manufacturing industry. This study closes a huge gap in the manufacturing industry, considering the importance of DF in other industries. Again, it contributes greatly by laying a strong foundation for future and emerging studies in this field. Also, utilizing the most current data in China and the fixed-effects and panel-threshold approaches to produce new evidence is crucial for developing the technological innovation of manufacturing firms in China and other parts of the world. The policy suggestions made will also be relevant to boosting DF in the manufacturing and technology sectors. Therefore, this article intends to fill this gap and make contributions by introducing market competition as a threshold variable, which will further enrich the relevant literature on the DF and MTI.

3. Theoretical Analysis and Hypotheses

3.1. The Impact of Digital Finance on Manufacturing Technology Innovation

Enterprise innovation activities are characterized by long cycles, high investment, strong uncertainty, and difficulty transforming results. They require a direct and effective supply of financial resources. DF incorporates advanced technologies such as big data, intelligence, the Internet of Things, mobile Internet, and cloud computing. These can make up for the shortcomings of traditional finance and assist manufacturing enterprises in carrying out innovative activities. First, DF can alleviate corporate resource mismatch [33] and meet the innovation needs of enterprises by integrating market resources and achieving reasonable allocation. At the same time, DF is conducive to correcting the problem of resource "domain mismatch" [3], which ensures sustainable fund injection for the innovation process in the manufacturing industry. Secondly, with the connectivity of the Internet, innovative elements such as knowledge and technology can freely flow, resulting in spillover effects. This enables enterprises to benefit from the innovation output of other enterprises and share achievements and resources. The open network characteristics of DF break the boundaries between manufacturing enterprises and promote collaborative innovation [34] and decrease innovation risk. Meanwhile, DF can effectively enhance the risk-bearing capacity of enterprises and enhance their innovation level. Furthermore, thanks to the smooth transmission of data and the rapid dissemination of information, DF assists enterprises in the real-time monitoring of market trends and obtaining feedback information, seizing innovation opportunities in a timely manner, accelerating the marketization process of innovation achievements, and creating profits for enterprises. This enhances their investment enthusiasm for innovation projects. In addition, DF can also act on the production process of the manufacturing industry, improve innovation efficiency through restructuring, and optimize manufacturing processes [32]. In summary, this paper proposes Hypothesis 1:

H1. *DF has a positive impact on MTI.*

3.2. Digital Finance, Financial Constraint, and Manufacturing Technology Innovation

Arslan [35] proposed that there are deficiencies in capital markets, including information asymmetry and agency costs. This results in differences in internal and external funding costs, eventually leading to financial constraints (FCs). The traditional financial system lacks risk-bearing capacity, making it difficult to effectively support the innovation process of enterprises. However, it is difficult to fill the funding gap of innovation activities by relying solely on internal financing. Also, companies facing FCs will choose to reduce innovation investment. DF is inclusive, low-cost, and convenient and can effectively solve the problem of FCs.

To begin with, DF eliminates geographical barriers and utilizes digital platforms to provide financial services to long-tail customers not covered by traditional finance. It can provide more financing channels for private and SMEs, reduce service access barriers, and expand innovative funding sources for enterprises. At the same time, the development of DF has compressed the profit space of commercial banks. This forces them to accelerate the pace of digital transformation and reduce financial exclusion, achieve service expansion increment through sinking businesses, and further expand enterprise financing channels. Secondly, DF expands the information contact between financial institutions and enterprises. It helps financial institutions to explore and integrate soft and unstructured information that is difficult to quantify by traditional finance, which contributes to obtaining an accurate portrayal of businesses. On the one hand, through multi-dimensional data analysis, DF deeply reforms the credit-risk pricing model of financial institutions and accurately identifies potential risks, which is conducive to alleviating the problem of adverse selection. On the other hand, DF can cover the whole process of enterprise credit granting, loan management, post-loan early warning, and overdue treatment. It can also create an intelligent and digital risk-control platform and realize dynamic monitoring and hierarchical disposal, thus reducing moral hazard. DF enhances the risk screening and evaluation capabilities of financial institutions and strengthens information transparency between banks and businesses. This helps to resolve the information asymmetry problem [36], thereby alleviating FCs. Finally, DF decreases finance costs. The application of digital technology reduces the demand for manpower and reduces labor costs. Also, the cross-regional and cross-platform financial service model breaks away from dependence on physical outlets and reduces infrastructure construction and maintenance costs. Big data and cloud computing technology also help enterprises to tap potential customer needs and achieve the accurate and efficient matching of supply and demand. This helps to reduce information processing costs and improve financing efficiency.

Based on the above analysis, DF can alleviate the FCs of enterprises in multiple ways, thereby providing sufficient liquidity for innovation activities. Therefore, this paper proposes Hypothesis 2:

H2. *FCs play a mediating role between DF and MTI.*

3.3. The Threshold Effect of Market Competition

As an external governance environment, market competition can affect the implementation of corporate R&D investment decisions. There is currently no unified view on whether competition promotes or suppresses innovation. Some scholars have concluded that competition can motivate enterprises to invest more in R&D and thus promote innovation [37], which is reflected in the "escape from competition effect". In highly competitive industries, the rule of "survival of the fittest" requires enterprises to maintain competitiveness and continuously strengthen technological innovation. The homogenization of products caused by competition motivates enterprises to accelerate their innovation pace. Again, some scholars have concluded that market competition suppresses corporate innovation [38], known as the "Schumpeter effect". The intense market competition may lead to the encroachment of a company's market share, thereby reducing investment in innovative projects that cannot generate profits in the short term. The deepening of market competition is also not conducive to promoting high-quality innovation for enterprises. Moreover, other scholars have concluded that there was an inverted U-shaped relationship between market competition and enterprise innovation [39,40]. Moderate competition can drive enterprise innovation, while excessive competition damages innovation enthusiasm. Competition enhances the uncertainty of research and development activities, and it is difficult to predict the innovative behavior of enterprises under different market structures. On the one hand, to maintain a competitive advantage, enterprises will accelerate the speed of new product development to obtain a "first mover advantage" [41]. At this point, manufacturing companies are more willing to use DF for innovative activities. On the other hand, fierce competition will squeeze the market space of enterprises. It will reduce the profitability of new products, inhibit the willingness of enterprises to put more investment into R&D funds, and thus weaken the driving effect of DF on innovation.

In summary, the technological innovation activities of firms can be influenced by the level of competition in the market, which in turn affects the role of digital finance. Based on the above summary, the technological innovation activities of enterprises could be influenced by the level of competition in the market, which in turn affects the role of DF. Therefore, this paper proposes Hypothesis 3:

H3. *There is a threshold effect based on market competition between DF and MTI.*

4. Research Design and Methodology

4.1. Variables Selection

4.1.1. Explained Variable

The explained variable is MTI. Technology innovation is measured using patent applications recorded regarding the listed firms [17]. The number of patent approvals provided the basis for the robustness test.

4.1.2. Explanatory Variable

The explanatory variable is DF. This paper uses the digital financial inclusion index of Peking University to measure the development level of DF [16,42]. Based on a comprehensive summary of the connotation and characteristics of DF, the development level of industries such as asset management, payment, banking, and insurance are systematically depicted by the index. This paper selects the provincial digital financial inclusion index and three sub-dimensional data and conducts logarithmic processing.

4.1.3. Mediating Variable

The mediating variable is FC. This paper selects the SA index to measure FC [43]. The index found that company size and age can reasonably estimate FC and are beneficial for reducing endogeneity. The specific expression form of this index is: $-0.737 \times$ size + $0.043 \times$ size2 $- 0.04 \times$ age. As the SA index increases, the FC faced by the firms deepens.

4.1.4. Threshold Variable

The threshold variable is market competition. The paper uses the Herfindahl–Hirschman Index (HHI) to measure market competition [44,45]; the specific expression form is:

$$\mathrm{HHI} = \sum \left(\frac{\mathrm{X_i}}{\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{X_i}} \right)^2 \tag{1}$$

where $\mathrm{X_i}$ represents the operating revenue of company i, $\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{X_i}$ represents the operating revenue of the industry to which company i belongs, and the ratio of the two is the industry share occupied by the company i. This index expresses the sum of squares of the ratio of the operating revenues of each company in the industry to the operating revenues of the industry. The higher the HHI value, the more concentrated the market is and the less competitive it is. This paper takes the opposite number of the HHI.

4.1.5. Control Variables

To alleviate the impact of missing variables, this paper refers to the practices of the previous literature [16] and selects control variables, including asset–liability ratio, corporate size, fixed assets, return on assets, growth, operating cash flow, proportion of independent directors, equity concentration, economic development level, and industrial structure. Table 1 depicts the specifics.

4.2. Sample Selection and Data Sources

This paper takes manufacturing companies listed in the Shanghai and Shenzhen A-shares as the research object, with a period of 2011–2020. Before the empirical analysis, the sample was processed as follows: (1) Special Treatment (ST) and Particular Transfer (PT) companies were excluded, (2) Samples with missing key variable data were removed, (3) A 1% tail reduction on continuous variables was performed. Finally, 1261 listed companies were obtained, comprising 12,610 observations. The financial data of the enterprise level are from the CSMAR database (CSMAR (gtarsc.com, accessed on 5 July 2023)), the data from the city level are from the China Statistical Yearbook, the patent data are from the CNRDS database (Chinese Research Data Services Platform (cnrds.com), accessed on 5 July 2023), and the digital financial index is the digital financial inclusion index of Peking University. Table 2 presents the descriptive statistical results of the main variables. It can be seen that there is a certain gap in the level of technological innovation among different manufacturing enterprises in China. There is an imbalance in the development of regional DF. Table 3 exhibits the correlation coefficients between variables. In addition, all of the variables' variance inflation factors are under 10, demonstrating that the multicollinearity problem does not exist.

Table 1. Variables descriptions.

Variable Type	Variable Name	Symbol	Measurement Indicators
explained variable	manufacturing technology innovation	TI	ln(1 + number of patent applications of listed companies)
explanatory variables	digital finance coverage breadth use depth digital degree	DF DFc DFu DFd	Peking University digital financial inclusion index
mediating variable	financial constraints	FC	SA index
threshold variable	market competition	HHI	Herfindahl–Hirschman Index
control variables	corporate size	size	ln(total assets)
	leverage	lev	total liabilities/total assets
	return on assets	ROA	net profit/total assets
	fixed assets	FA	net fixed assets/total assets
	growth	growth	(operating income of current year-operating income of last year)/operating income of last year
	operating cash flow	CF	net operating cash flow/total assets
	proportion of independent directors	Indd	number of independent directors/total number of directors
	equity concentration	Tops	shareholding ratio of the largest shareholder
	economic development level	GDP	ln(Per capita GDP)
	industrial structure	IS	output value of secondary sector of the economy/GDP

NB: TI is manufacturing technology innovation, DF is Digital finance, DFc is digital finance coverage breadth, DFu is digital finance use depth, DFd is digital finance digital degree, FC is financial constraints, HHI market competition, ROA is return on assets, FA is fixed assets, CF is operating cash flow, Indd is proportion of independent directors, Tops is equity concentration, GDP is economic development level, and IS is industrial structure.

4.3. Model Building

To study the impact of DF on MTI, this paper establishes the following model:

$$\mathrm{TI}_{i,t} = \alpha_0 + \alpha_1 \mathrm{DF}_{i,t} + \alpha_2 \sum \mathrm{Controls}_{i,t} + \sum \mathrm{Year} + \sum \mathrm{Industry} + \varepsilon_{i,t} \quad (2)$$

where TI is MTI, DF is digital finance, Controls represent control variables, $\varepsilon_{i,t}$ is a random error term, i and t represent the company and year, respectively. This paper controls the industry and the year—the fixed effects—in the model.

To verify Hypothesis 2, this model is formulated:

$$\mathrm{Mediator}_{i,t} = \beta_0 + \beta_1 \mathrm{DF}_{i,t} + \beta_2 \sum \mathrm{Controls}_{i,t} + \sum \mathrm{Year} + \sum \mathrm{Industry} + \varepsilon_{i,t} \quad (3)$$

where Mediator stands for mediating variable, i.e., FC.

To verify Hypothesis 3, the paper uses Hansen's panel-threshold model [46]. This model can better describe the non-linear relationship between variables. Equation (4) shows this:

$$\begin{aligned}\mathrm{TI}_{i,t} = \lambda_0 + \lambda_1 \mathrm{DF}_{i,t} \times \mathrm{I}\left(q_{i,t} \le \gamma\right) + \lambda_2 \mathrm{DF}_{i,t} \times \mathrm{I}\left(q_{i,t} \ge \gamma\right) + \lambda_3 \sum \mathrm{Controls}_{i,t} \\ + \sum \mathrm{Year} + \sum \mathrm{Industry} + \varepsilon_{i,t}\end{aligned} \quad (4)$$

where $q_{i,t}$ is the threshold variable, i.e., market competition, γ is the threshold value, and I is the indicative function.

Table 2. Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
TI	12,610	3.197	1.681	0.000	7.296
DF	12,610	5.321	0.597	3.381	6.038
DFc	12,610	5.213	0.661	2.706	5.982
DFu	12,610	5.348	0.553	3.439	6.102
DFd	12,610	5.498	0.737	2.816	6.112
size	12,610	22.165	1.213	19.658	25.675
lev	12,610	0.423	0.207	0.051	0.969
ROA	12,610	0.032	0.066	−0.279	0.197
FA	12,610	0.238	0.144	0.010	0.642
growth	12,610	0.147	0.391	−0.575	2.499
CF	12,610	0.044	0.067	−0.157	0.233
Indd	12,610	0.374	0.053	0.333	0.571
Tops(%)	12,610	32.911	14.010	8.480	71.240
GDP	12,610	11.272	0.525	9.928	12.153
IS(%)	12,610	43.704	10.826	16.200	66.990

NB: TI is manufacturing technology innovation, DF is Digital finance, DFc is digital finance coverage breadth, DFu is digital finance use depth, DFd is digital finance digital degree, ROA is return on assets, FA is fixed assets, CF is operating cash flow, Indd is proportion of independent directors, Tops is equity concentration, GDP is economic development level, and IS is industrial structure.

Table 3. Correlation coefficient.

	TI	DF	size	lev	ROA	FA	growth	CF	Indd	Tops	GDP	IS
TI	1											
DF	0.254 ***	1										
size	0.549 ***	0.223 ***	1									
lev	0.144 ***	0.011	0.407 ***	1								
ROA	0.116 ***	−0.074 ***	0.086 ***	−0.372 ***	1							
FA	−0.110 ***	−0.044 ***	0.121 ***	0.172 ***	−0.119 ***	1						
growth	0.040 ***	−0.056 ***	0.038 ***	0.001	0.240 ***	−0.060 ***	1					
CF	0.098 ***	0.128 ***	0.155 ***	−0.138 ***	0.378 ***	0.198 ***	0.011	1				
Indd	0.002	0.061 ***	0.020 **	0.002	−0.052 ***	−0.020 **	−0.012	−0.021 **	1			
Tops	0.052 ***	−0.121 ***	0.173 ***	0.01	0.141 ***	0.039 ***	0.026 ***	0.092 ***	0.043 ***	1		
GDP	0.235 ***	0.428 ***	0.104 ***	−0.024 ***	−0.005	−0.155 ***	−0.004	0.033 ***	0.038 ***	−0.011	1	
IS	−0.134 ***	−0.370 ***	−0.109 ***	0.005	0.031 ***	0.177 ***	−0.001	0.006	−0.050 ***	−0.028 ***	−0.268 ***	1

Notes: **, and *** denotes significance at 10%, 5%, and 1%, respectively. TI is manufacturing technology innovation, DF is Digital finance, ROA is return on assets, FA is fixed assets, CF is operating cash flow, Indd is proportion of independent directors, Tops is equity concentration, GDP is economic development level, and IS is industrial structure.

5. Empirical Analysis

5.1. Benchmark Regression Analysis

This paper uses Equation (2) to verify Hypothesis 1, and the specific regression results are shown in Table 4. Columns (1) and (2) show the regression results of DF on MTI. In Column 1, control variables are not included. It can be seen that DF has a significant positive impact on technological innovation before and after adding control variables. The second column indicates that for every unit of growth in DF, the MTI level of manufacturing enterprises increases by 0.302 units, which is a positive indication. Hypothesis 1 is validated. DF can break down information barriers, unblock enterprise information and capital flows, and inject capital into manufacturing enterprise innovation activities. At the same time, financial institutions use digital technologies to enhance the capabilities of data screening, identification, and analysis, improve resource-allocation efficiency, and increase investment in high-quality innovation projects. Therefore, DF can promote MTI in manufacturing enterprises.

Table 4. Impact of DF on MTI.

			TI		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
DF	0.564 ***	0.302 ***			
	(6.95)	(3.79)			
DFc			0.086 *		
			(1.85)		
DFu				0.445 ***	
				(7.29)	
DFd					0.025
					(0.45)
size		0.791 ***	0.791 ***	0.791 ***	0.791 ***
		(70.48)	(70.38)	(70.63)	(70.27)
lev		−0.409 ***	−0.423 ***	−0.385 ***	−0.434 ***
		(−5.77)	(−5.96)	(−5.44)	(−6.13)
ROA		1.818 ***	1.821 ***	1.800 ***	1.825 ***
		(8.12)	(8.13)	(8.04)	(8.15)
FA		−0.496 ***	−0.493 ***	−0.506 ***	−0.488 ***
		(−5.06)	(−5.02)	(−5.18)	(−4.97)
growth		−0.024	−0.024	−0.023	−0.025
		(−0.75)	(−0.76)	(−0.72)	(−0.78)
CF		0.676 ***	0.700 ***	0.634 ***	0.710 ***
		(3.36)	(3.48)	(3.16)	(3.53)
Indd		−0.765 ***	−0.764 ***	−0.768 ***	−0.763 ***
		(−3.69)	(−3.68)	(−3.71)	(−3.67)
Tops		−0.0008	−0.0008	−0.0008	−0.0008
		(−0.93)	(−0.89)	(−0.93)	(−0.86)
GDP		0.108 ***	0.133 ***	0.072 ***	0.152 ***
		(4.02)	(5.13)	(2.74)	(6.38)
IS		0.0005	−0.0001	0.0007	−0.0007
		(0.46)	(−0.12)	(0.56)	(−0.57)
_cons	0.195	−16.670 ***	−15.760 ***	−17.050 ***	−15.630 ***
	(0.45)	(−35.54)	(−40.20)	(−40.95)	(−31.09)
Year	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes
N	12,610	12,610	12,610	12,610	12,610
adj. R^2	0.215	0.493	0.493	0.495	0.493

Notes: *, and *** denotes significance at 10%, and 1%, respectively. t-statistics are shown in (). TI is manufacturing technology innovation, DF is Digital finance, DFc is digital finance coverage breadth, DFu is digital finance use depth, DFd is digital finance digital degree, ROA is return on assets, FA is fixed assets, CF is operating cash flow, Indd is proportion of independent directors, Tops is equity concentration, GDP is economic development level, and IS is industrial structure.

Columns (3), (4), and (5), respectively, exhibit the regression outcomes of the three sub-indicators of DF on technological innovation. The results show that the coefficients for coverage breadth and depth of use are 0.086 and 0.445, respectively, and are significant. This proves that these two factors can encourage technological innovation. On the one hand, manufacturing enterprises benefit from expanding financial service coverage and can receive sufficient funds for innovation activities, thereby improving innovation output. On the other hand, with the help of technologies such as big data and cloud computing, DF can provide enterprises with more-diversified and precise financial services, such as credit, investment strategy analysis, credit evaluation, and other businesses, thus helping to improve their financing ability and innovation enthusiasm. The coefficient of digitalization shown in Column (5) is 0.025, but there is no significant difference, indicating that although the mobility, creditability, and convenience associated with DF can reduce the financing costs of manufacturing enterprises and help them promote innovative projects, it has not benefited manufacturing enterprises. The above analysis indicates that the process of promoting technological innovation by DF is achieved by integrating multiple factors. To enhance corporate innovation capabilities in manufacturing companies, it is necessary to assist them in deeply utilizing DF.

5.2. Mechanism Analysis

The previous analysis has confirmed that DF can promote manufacturing technological innovation. The following analyzes the mechanism. From Column (1) of Table 5, it can be seen that the coefficient of DF is significantly negative, with a value of −0.070, indicating that DF reduces the FCs of manufacturing enterprises. Column (2) shows that FC inhibits technological innovation. Therefore, DF can stimulate enterprise innovation by alleviating FCs. The reason for this is that DF has broadened financing channels, which is helpful for manufacturing enterprises to squeeze out more funds for innovation activities. Notwithstanding, based on Internet platforms, DF can mine and analyze the non-standard transaction data of enterprises, improve the quality of enterprise information disclosure, enhance information transparency between banks and enterprises, and reduce information asymmetry. The inclusive and low-cost characteristics of DF can effectively alleviate FC, provide sufficient funds for innovation activities of manufacturing enterprises, and facilitate the smooth implementation of technological innovation projects.

Table 5. Channel testing of FC.

	FC	**TI**
	(1)	(2)
DF	−0.070 ***	
	(−5.01)	
FC		−0.455 ***
		(−9.77)
size	0.020 ***	0.800 ***
	(7.68)	(70.98)
lev	0.340 ***	−0.276 ***
	(26.03)	(−3.79)
ROA	0.191 ***	1.911 ***
	(4.26)	(8.55)
FA	−0.019	−0.498 ***
	(−1.04)	(−5.10)
growth	−0.034 ***	−0.041
	(−5.16)	(−1.27)
CF	0.019	0.715 ***
	(0.51)	(3.57)
Indd	−0.286 ***	−0.892 ***
	(−7.10)	(−4.30)
Tops	−0.0009 ***	−0.001
	(−5.69)	(−1.35)

Table 5. *Cont.*

	FC	TI
GDP	−0.038 ***	0.130 ***
	(−8.00)	(5.43)
IS	−0.0007 ***	−0.0008
	(−3.19)	(−0.75)
_cons	4.237 ***	−13.680 ***
	(45.57)	(−32.61)
Year	Yes	Yes
Industry	Yes	Yes
N	12,610	12,610
adj. R^2	0.178	0.496

Notes: *** is 1% significance level. TI is manufacturing technology innovation, DF is Digital finance, FC is financial constraints, ROA is return on assets, FA is fixed assets, CF is operating cash flow, Indd is proportion of independent directors, Tops is equity concentration, GDP is economic development level, and IS is industrial structure.

5.3. Threshold Effect Analysis

The previous empirical analysis has concluded that DF promotes MTI in manufacturing enterprises. Considering that the innovative driving role of DF in the real environment is influenced by market structure factors, there may be a non-linear relationship between DF and technological innovation. Therefore, based on the analysis of Hypothesis 3, this article takes market competition as a threshold variable and establishes a panel-threshold model for empirical analysis. This helps to further understand the nonlinear impact of DF on technological innovation.

The F-statistic tests of the single-threshold and dual-threshold models for market competition are shown in Table 6. The results show that the *p*-value of the single-threshold test is 0.070, and the *p*-value of the dual-threshold effect test is 0.087. Both pass the 10% significance level, while the *p*-value of the triple-threshold effect test does not pass the significance level. This indicates a dual-threshold effect based on market competition between DF and technological innovation, with threshold values of −0.083 and −0.028. Hypothesis 3 is validated. Figure 1 shows the forming process of the confidence intervals and threshold figures. Based on the determination of threshold values and threshold models, Table 6 shows the regression results with market competition as the threshold variable. It can be seen that when market competition is less than the first threshold value of −0.083, the coefficient of DF is 0.158, passing the significance level of 1%. When market competition is greater than −0.083 but less than −0.028, the DF coefficient is 0.135, which is significant at the 1% level. When market competition exceeds −0.028, the coefficient of DF is 0.110. As market competition gradually deepens, the promotion effect of DF on technological innovation becomes weaker. Intense competition may cause manufacturing enterprises to face more uncertain situations, thereby increasing the difficulty of predicting and implementing innovative projects. The increase in raw material costs brought on by competition squeezes the profit space that enterprises can obtain. It also reduces internally available surplus, enhances the preventive cash incentives of enterprises, and weakens innovation enthusiasm (Table 7).

Table 6. Threshold effect test.

Threshold Variables	Type	Threshold Value	Confidence Interval	*f* Value	*p* Value	10% Critical Value	5% Critical Value	1% Critical Value
HHI	single threshold	−0.028	[−0.083, −0.026]	19.34	0.070	17.931	20.947	27.328
	double threshold	−0.083	[−0.087, −0.083]	17.14	0.087	16.110	19.725	26.203
	triple threshold	−0.101	[−0.106, −0.091]	11.12	0.700	27.973	31.937	41.302

Note: HHI market competition.

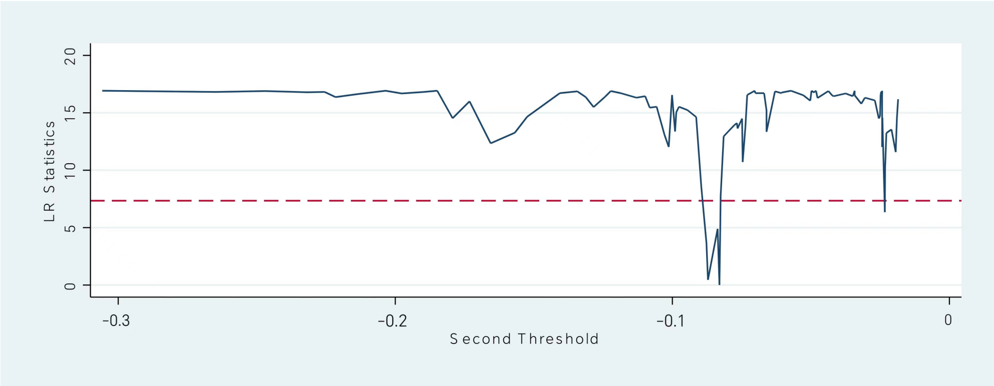

Figure 1. LR Function diagram.

Table 7. Threshold model regression results.

	TI (1)
size	0.703 ***
	(16.83)
lev	−0.386 **
	(−3.08)
ROA	0.311
	(1.59)
FA	−0.210
	(−1.14)
growth	0.028
	(1.15)
CF	0.007
	(0.05)
Indd	−0.594
	(−1.93)
Tops	−0.003
	(−1.39)
GDP	0.297 **
	(3.20)
IS	−0.019 ***
	(−5.52)
0._cat#c.DF	0.158 ***
	(4.49)
1._cat#c.DF	0.135 ***
	(3.86)
2._cat#c.DF	0.110 **
	(3.20)
_cons	−15.140 ***
	(−12.26)
N	12,610
R^2	0.352

Notes: ** and *** are 5% and 1% significance level respectively. TI is manufacturing technology innovation, ROA is return on assets, FA is fixed assets, CF is operating cash flow, growth is growth, Indd is proportion of independent directors, Tops is equity concentration, GDP is economic development level, and IS is industrial structure.

5.4. Robust Test

5.4.1. Replacing the Dependent Variable

To analyze whether the measurement indicators of MTI impact the empirical results, the number of patent authorizations of listed companies was selected to measure technology innovation. The regression results after replacing the indicators are shown in Table 8. It can be seen that the coefficients of DF are significantly positive after replacing the indicators. This proves the robustness and concludes that DF promotes MTI in manufacturing enterprises.

Table 8. Regression results of measuring technology innovation by the number of patent authorizations.

	TI				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
DF	0.504 ***	0.305 ***			
	(6.42)	(3.88)			
DFc			0.083		
			(1.62)		
DFu				0.477 ***	
				(7.38)	
DFd					0.024
					(0.39)
size		0.739 ***	0.739 ***	0.739 ***	0.738 ***
		(69.12)	(68.99)	(69.35)	(68.87)
lev		−0.325 ***	−0.340 ***	−0.304 ***	−0.349 ***
		(−4.88)	(−5.10)	(−4.58)	(−5.26)
ROA		1.117 ***	1.121 ***	1.096 ***	1.124 ***
		(5.30)	(5.31)	(5.21)	(5.32)
FA		−0.476 ***	−0.471 ***	−0.486 ***	−0.468 ***
		(−5.17)	(−5.11)	(−5.29)	(−5.07)
growth		−0.076 **	−0.077 **	−0.076 *	−0.077 **
		(−2.56)	(−2.58)	(−2.56)	(−2.59)
CF		0.716 ***	0.740 ***	0.671 ***	0.749 ***
		(3.85)	(3.98)	(3.61)	(4.03)
Indd		−0.448 **	−0.446 **	−0.446 **	−0.445 **
		(−2.30)	(−2.29)	(−2.29)	(−2.28)
Tops		0.0003	0.0003	0.0003	0.0004
		(0.36)	(0.40)	(0.34)	(0.43)
GDP		0.094 ***	0.121 ***	0.056 **	0.139 ***
		(3.66)	(4.84)	(2.18)	(6.09)
IS		0.002	0.001	0.002	0.001
		(1.56)	(0.94)	(1.71)	(0.51)
_cons	0.211	−15.890 ***	−14.970 ***	−16.410 ***	−14.840 ***
	(0.51)	(−35.03)	(−38.98)	(−40.16)	(−28.78)
Year	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes
N	12,610	12,610	12,610	12,610	12,610
adj. R2	0.222	0.487	0.487	0.489	0.487

Notes: *, ** and *** are 10%, 5% and 1% significance level respectively. TI is manufacturing technology innovation, DF is Digital finance, DFc is digital finance coverage breadth, DFu is digital finance use depth, DFd is digital finance digital degree, ROA is return on assets, FA is fixed assets, CF is operating cash flow, Indd is proportion of independent directors, Tops is equity concentration, GDP is economic development level, and IS is industrial structure.

5.4.2. Tobit Model

Given that some listed companies have zero patent applications, the Tobit model for robustness testing was selected. This is suitable for analyzing truncated data with zero value accumulation. The regression results after replacing the model can be seen in Table 9. The coefficients of DF, coverage breadth, and depth of use are significantly positive. The results depict that DF has a significant enhancement effect on technological innovation, and the conclusion is robust.

Table 9. Results of the Tobit model.

	TI			
	(1)	**(2)**	**(3)**	**(4)**
DF	1.203 **			
	(2.05)			

Table 9. *Cont.*

	TI			
	(1)	**(2)**	**(3)**	**(4)**
DFc		0.481 *		
		(1.77)		
DFu			1.281 **	
			(2.87)	
DFd				−0.244
				(−0.78)
size	2.350 ***	2.349 ***	2.345 ***	2.350 ***
	(13.11)	(13.10)	(13.11)	(13.09)
lev	−2.598 ***	−2.617 ***	−2.539 ***	−2.665 ***
	(−4.94)	(−4.97)	(−4.83)	(−5.06)
ROA	1.437	1.414	1.477	1.406
	(1.17)	(1.15)	(1.20)	(1.14)
FA	−0.264	−0.250	−0.285	−0.259
	(−0.37)	(−0.35)	(−0.40)	(−0.36)
growth	0.108	0.113	0.112	0.111
	(0.66)	(0.68)	(0.68)	(0.68)
CF	1.437	1.464	1.404	1.456
	(1.30)	(1.33)	(1.27)	(1.32)
Indd	−2.781	−2.831	−2.803	−2.792
	(−1.59)	(−1.62)	(−1.61)	(−1.60)
Tops	−0.007	−0.006	−0.007	−0.006
	(−0.75)	(−0.71)	(−0.76)	(−0.68)
GDP	0.121	0.177	0.0953	0.279
	(0.40)	(0.60)	(0.32)	(0.97)
IS	0.008	0.005	0.007	0.002
	(0.54)	(0.39)	(0.51)	(0.12)
_cons	−52.350 ***	−48.610 ***	−52.390 ***	−45.360 ***
	(−8.50)	(−8.75)	(−8.94)	(−7.87)
sigma_u	3.986 ***	3.998 ***	3.960 ***	4.010 ***
	(15.26)	(15.27)	(15.26)	(15.27)
sigma_e	3.138 ***	3.137 ***	3.140 ***	3.137 ***
	(18.55)	(18.55)	(18.56)	(18.54)
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
N	12,610	12,610	12,610	12,610

Notes: *, ** and *** are 10%, 5% and 1% significance level respectively. TI is manufacturing technology innovation, DF is Digital finance, DFc is digital finance coverage breadth, DFu is digital finance use depth, DFd is digital finance digital degree, ROA is return on assets, FA is fixed assets, CF is operating cash flow, Indd is proportion of independent directors, Tops is equity concentration, GDP is economic development level, and IS is industrial structure.

5.4.3. Endogeneity Testing

Considering the potential endogeneity issues caused by missing variables and reverse causal relationships during the model setting process, inferences were made from Yao and Luo et al. [16,47], and the Internet penetration rate and spherical distance between cities and Hangzhou as instrumental variables of DF were selected. The data on the Internet penetration rate come from the China Internet Information Center, and the distance from each city to Hangzhou is calculated using STATA 15 software. On the one hand, the development of DF is closely related to the Internet, and there is no direct transmission path between the regional Internet penetration rate and MTI. On the other hand, Hangzhou is the birthplace of digital financial service platforms such as Alibaba and Ant Financial. The development of DF in cities that are closer to Hangzhou is more mature. There is no direct connection between the enterprise's MTI and the distance from each city to Hangzhou. Therefore, the selection of two instrumental variables is reasonable. The specific regression results are shown in Table 10. Columns (1) and (2) are the regression results of the distance from each city to Hangzhou (HZ) as an instrumental variable, and Columns (3) and (4) are the results of the Internet penetration rate (net). It can be seen that the Kleibergen–Paap rk LM statistic in both cases is significant at the 1% level. At the same time, the weak instrumental variables test shows that the Kleibergen–Paap–Wald rk F statistic value exceeds the critical value of 16.38, indicating no problem of insufficient identification and weak instrumental variables. The regression coefficient of DF after adding instrumental variables is still significantly positive, which proves that DF can drive the technology innovation of manufacturing firms, consistent with the threshold regression results.

Table 10. Endogeneity test results.

	DF	**TI**	**DF**	**TI**
	(1)	**(2)**	**(3)**	**(4)**
DF		1.222 *		0.248 **
		(1.95)		(2.22)
	0.001 ***			
	(7.83)			
net			0.010 ***	
			(76.93)	
size	−0.002	0.769 ***	−0.004 ***	0.759 ***
	(−1.57)	(60.17)	(−3.72)	(77.06)
lev	−0.079 ***	−0.225 **	−0.001 *	0.013 **
	(−10.18)	(−2.45)	(−1.80)	(2.14)
ROA	−0.011	1.094 ***	0.064 ***	2.248 ***
	(−0.48)	(4.46)	(3.14)	(10.63)
FA	−0.009	−1.657 ***	0.014 *	−0.582 ***
	(−0.99)	(−16.76)	(1.61)	(−6.02)
growth	−0.002	0.040	−0.004	−0.0409
	(−0.77)	(1.07)	(−1.53)	(−1.26)
CF	0.111 ***	0.058	0.038 ***	0.781 ***
	(4.98)	(0.25)	(1.95)	(3.84)
Indd	0.014	−0.542 **	−0.035 *	−0.696 ***
	(0.59)	(−2.35)	(−1.70)	(−3.46)
Tops	0.000	−0.004 ***	0.0003 ***	−0.001
	(0.64)	(−4.12)	(3.58)	(−1.61)
GDP	0.145 ***	0.247 **	0.033 ***	0.0747 ***
	(53.57)	(2.52)	(14.46)	(3.47)
IS	−0.004 ***	0.006 **	0.0003 **	−0.00003
	(−30.17)	(2.17)	(2.45)	(−0.03)
N	12,610	12,610	12,610	12,610
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Chi-sq(1) *p* value	0.000	0.000	0.000	0.000
Kleibergen–Paap rk LM statistic		339.39		1562.26
p value		0.000		0.000
Kleibergen–Paap–Wald rk F statistic		61.30		5918.19
Stock–Yogo weak ID test critical values		[16.38]		[16.38]
adj. R^2		0.321		0.363

Notes: *, ** and *** are 10%, 5% and 1% significance level respectively. TI is manufacturing technology innovation, DF is Digital finance, ROA is return on assets, FA is fixed assets, CF is operating cash flow, Indd is proportion of independent directors, Tops is equity concentration, GDP is economic development level, and IS is industrial structure.

5.5. Heterogeneity Analysis

It has been established in the earlier discussion that DF can promote MTI in the manufacturing industry. However, it has not been confirmed whether there are differences in this promotion effect under different conditions. To determine this, heterogeneity analysis was conducted based on regions, enterprise nature, and factor-intensive types.

5.5.1. Regional Heterogeneity

When China's vast territory is considered, there are significant differences in the development level of DF among different regions, which may lead to regional heterogeneity in the impact of DF on MTI. Samples are grouped based on the registered address of the listed company, namely, the Eastern Region (ER), the Central Region (CR), and the Western Region (WR). The specific regression results are shown in Table 11. It can be seen that the regression coefficient of DF in the ER is 0.176 and is not significant. The coefficients of the CR and WR are 2.062 and 1.969, respectively, both of which are significant at the 1% level. At the same time, the p-value of the inter-group coefficient test confirms that the coefficient difference of DF is significant. The results indicate that compared to the Eastern Region, DF is more capable of driving MTI in the Central and Western regions. The ER of China has advanced technological and financial resource endowments, including urban agglomerations such as Beijing Tianjin Hebei, the Yangtze River Delta, and the Pearl River Delta. It has a strong industrial foundation and attracts talent, capital, and industrial agglomeration. The eastern region has "hard power", such as manufacturing plants, and the engages in the construction of "soft power", such as business environment and system supply, which can provide more R&D support for manufacturing enterprises. However, the monetary development in the CR and WR is relatively slow, especially with high financial supply costs and low physical network coverage. Traditional finance cannot fully meet the innovation needs of enterprises, resulting in insufficient innovation capacity in the local manufacturing industry. The geographically unrestricted nature of DF can extend its service scope to the CR and WR, lower the financial access threshold of vulnerable groups, and provide more opportunities for local manufacturing enterprises to innovate. At the same time, the cross-platform and cross-regional advantages of DF can enhance the liquidity and utilization of innovative elements such as knowledge, technology, and capital. DF can also provide sufficient innovation resources for enterprises in the CR and WR. In the Central and Western regions, manufacturing enterprises that do not have innovation power will make more active use of DF, and their innovation power and ability will be enhanced. Therefore, compared to the Eastern region, DF can bring more significant innovation output growth to manufacturing enterprises in the Central and Western regions.

Table 11. Regression results of regional heterogeneity.

	TI		
	The Eastern Region	**The Central Region**	**The Western Region**
DF	0.176	2.062 ***	1.969 ***
	(1.45)	(4.65)	(5.48)
size	0.830 ***	0.727 ***	0.762 ***
	(58.88)	(28.65)	(28.12)
lev	−0.421 ***	−0.625 ***	−0.320
	(−5.11)	(−4.30)	(−1.93)
ROA	1.924 ***	1.305 **	1.368 **
	(7.35)	(2.90)	(2.67)
FA	−0.210	−0.633 **	−0.973 ***
	(−1.86)	(−2.96)	(−4.92)
growth	0.029	−0.049	−0.091
	(0.75)	(−0.83)	(−1.48)
CF	1.000 ***	−0.285	0.438
	(4.38)	(−0.70)	(0.95)
Indd	−0.493 *	−1.846 ***	−0.101
	(−1.98)	(−4.11)	(−0.19)
Tops	−0.002 *	0.006 **	−0.002
	(−2.16)	(2.92)	(−0.95)

Table 11. *Cont.*

	TI		
	The Eastern Region	**The Central Region**	**The Western Region**
GDP	0.153 ***	0.421 ***	−0.217 **
	(4.52)	(7.08)	(−2.97)
IS	−0.002	0.003	−0.010 **
	(−1.69)	(0.77)	(−2.96)
_cons	−16.470 ***	−25.670 ***	−17.690 ***
	(−18.54)	(−15.21)	(−10.74)
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
N	8130	2490	1990
adj. R^2	0.509	0.493	0.515
p-value of inter-group	E and C	E and W	W and C
difference test	0.000	0.000	0.450

Notes: *, ** and *** are 10%, 5% and 1% significance level respectively. TI is manufacturing technology innovation, DF is Digital finance, ROA is return on assets, FA is fixed assets, CF is operating cash flow, Indd is proportion of independent directors, Tops is equity concentration, GDP is economic development level, and IS is industrial structure.

5.5.2. Heterogeneity of Enterprise Nature

Table 12 exhibits the regression outcomes of the enterprise nature group. The coefficient of DF in the state-owned enterprise group is 0.221, making it significant at the 10% level. The coefficient in non-state-owned enterprises is 0.413 and is significant at the 1% level. The *p*-value of the inter-group coefficient test is 0.07, which is significant at the 10% level. This indicates that the coefficient difference between the enterprise nature group is significant. Also, DF can better promote the technological innovation level of non-state-owned manufacturing firms. Government-owned firms have an advantageous position in resource acquisition. Policy support and assistance from financial institutions make it easier to obtain funds, while non-state-owned enterprises face more credit discrimination and have fewer opportunities to access formal financing channels. Asymmetric information hinders traditional financial institutions from grasping the financial situation of private enterprises, which poses obstacles in evaluating their credit repayment. So, situations such as reluctance and prudence in lending have left non-state-owned enterprises in long-term financing difficulties. The insufficient support of traditional finance for private enterprises has made them more dependent on DF. DF can deeply enhance the financing atmosphere of non-state-owned firms, change the credit preferences of financial institutions, and guide the flow of financial resources to non-state-owned enterprises. With the help of DF, the extremely low marginal cost can reduce the funding burden of non-state-owned firms and advance the funding efficiency of firms. At the same time, DF can leverage the advantage of precise resource allocation to provide more financial support for the innovation of non-state-owned manufacturing enterprises. Therefore, compared to state-owned enterprises with advantageous positions, the characteristics of DF correspond to the innovation needs of non-state-owned firms and can motivate them to carry out technological innovation activities.

Table 12. Regression results of heterogeneity in enterprise nature.

	TI	
	Non-State-Owned Enterprises	**State-Owned Enterprise**
DF	0.413 ***	0.221 *
	(4.47)	(1.86)
size	0.753 ***	0.738 ***
	(48.73)	(45.41)
lev	−0.264 ***	−0.261 **
	(−2.88)	(−2.31)

Table 12. *Cont.*

	TI	
	Non-State-Owned Enterprises	**State-Owned Enterprise**
ROA	1.807 ***	2.251 ***
	(6.49)	(6.10)
FA	−0.253 **	−0.599 ***
	(−1.97)	(−4.03)
growth	−0.046	0.051
	(−1.08)	(1.06)
CF	0.682 ***	−0.086
	(2.82)	(−0.35)
Indd	−0.334	−0.996 ***
	(−1.29)	(−3.19)
Tops	0.000	−0.005 ***
	(0.17)	(−3.59)
GDP	0.075 ***	0.056 *
	(3.00)	(1.75)
IS	0.004 **	−0.003
	(2.23)	(−1.63)
_cons	−16.480 ***	−14.110 ***
	(−27.32)	(−20.86)
Year	Yes	Yes
Industry	Yes	Yes
N	7700	4910
adj. R^2	0.448	0.569
p-value of inter group difference test	0.070	

Notes: *, ** and *** are 10%, 5% and 1% significance level respectively. TI is manufacturing technology innovation, DF is Digital finance, ROA is return on assets, FA is fixed assets, CF is operating cash flow, Indd is proportion of independent directors, Tops is equity concentration, GDP is economic development level, and IS is industrial structure.

5.5.3. Factor-Intensive Type Heterogeneity

Based on the standards of the Chinese Bureau of Statistics for the manufacturing industry, this article refers to the classification method of manufacturing industry types by Yang et al. [48]. The manufacturing industry has also been divided into three categories: labor-intensive, capital-intensive, and technology-intensive. The specific classification content is shown in Table 13. Table 14 exhibits the regression outcome of the factor-intensive group. The coefficient of DF under the labor-intensive group is 0.788, which is significant at the 1% level. The coefficient of the capital-intensive group is 0.335, which is significant at the 5% level, while the coefficient of the technology-intensive group is negative and not significant. This indicates that DF has the strongest promoting effect on technological innovation in labor-intensive manufacturing enterprises, followed by capital-intensive enterprises, while there is no significant promoting effect on technology-intensive enterprises. DF can alleviate financing constraints, help labor-intensive enterprises introduce machinery and equipment to reduce their dependence on labor, and promote automated production to improve production efficiency. The reduction in labor supply caused by the decline in demographic dividends forced the transformation and upgrading of the labor-intensive manufacturing industry. In addition, the development process of capital-intensive manufacturing requires a large amount of investment. DF can promote industrial clusters, achieve collaborative innovation between upstream and downstream industrial chains, and help reduce manufacturing costs. DF helps investment entities comprehensively understand the credit status of enterprises and improve financing efficiency. At the same time, capital-intensive enterprises can accelerate capital turnover and improve capital-utilization efficiency by accepting payment, credit, investment, and other services provided by DF, thereby improving the cash flow management level of enterprises. Finally, for technology-intensive manufacturing enterprises, DF has not shown significant incentive effects. The key core technologies of China's high-tech manufacturing industry are lacking, and high-end components rely on imports. At the same time, the technology research and development process of this industry requires a huge amount of funds and knowledge reserves, and innovation results require marketization to create profits for enterprises. The assistance of DF in R&D investment and achievement transformation for technology-intensive enterprises is not sufficient. This hinders and shortens their ability to improve the innovation level of such enterprises.

Table 13. Classification of the manufacturing industry based on factor-intensive types.

Types	Specific Industries
Labor-intensive	Agricultural and sideline food processing industry; food manufacturing industry; textile industry; textile clothing and clothing industry; leather, fur, feather and its products and shoemaking industry; wood processing and wood; bamboo, rattan, palm and grass products industry; furniture manufacturing industry; printing and recording media reproduction industry; culture and education; arts and crafts; sports and entertainment supplies manufacturing industry; rubber and plastic products industry; non-metallic mineral products industry; metal products industry; other manufacturing industries; waste resources comprehensive utilization industry; machinery and equipment repair industry
Capital-intensive	Wine and beverage and refined tea manufacturing industry; paper making and paper products industry; petroleum processing and coking and nuclear fuel processing industry; chemical raw materials and chemical products manufacturing industry; chemical fiber manufacturing industry; ferrous smelting and rolling processing industry; nonferrous metal smelting and rolling processing industry; general equipment manufacturing industry
Technology-intensive	Pharmaceutical manufacturing industry; specialized equipment manufacturing industry; automotive manufacturing industry; railway, ship, aerospace, and other transportation equipment manufacturing industry; electrical machinery and equipment manufacturing industry; computer and other electronic equipment manufacturing industry; instrument and meter manufacturing industry

Table 14. Regression results of factor-intensive type group.

		TI	
	Labor-Intensive	**Capital-Intensive**	**Technology-Intensive**
DF	0.788 ***	0.335 **	−0.121
	(4.23)	(2.33)	(−1.09)
size	0.671 ***	0.710 ***	0.883 ***
	(20.96)	(37.09)	(61.33)
lev	−0.522 ***	−0.757 ***	−0.139
	(−2.92)	(−6.10)	(−1.46)
ROA	2.972 ***	0.911 **	1.668 ***
	(5.11)	(2.25)	(5.64)
FA	−0.274	−0.866 ***	−0.081
	(−1.18)	(−5.44)	(−0.56)
growth	−0.083	0.012	−0.034
	(−0.94)	(0.20)	(−0.82)
CF	0.639	0.086	1.133 ***
	(1.36)	(0.25)	(4.00)
Indd	−1.715 ***	−0.495	−0.622 **
	(−3.41)	(−1.21)	(−2.35)
Tops	0.003	0.002	−0.003 ***
	(1.24)	(1.25)	(−2.65)
GDP	0.092	0.093 *	0.187 ***
	(1.34)	(1.93)	(5.42)
IS	−0.005	−0.011 ***	0.008 ***
	(−1.61)	(−4.75)	(5.16)
_cons	−16.330 ***	−14.620 ***	−17.440 ***
	(−13.35)	(−17.92)	(−27.08)

Table 14. *Cont.*

	TI		
	Labor-Intensive	**Capital-Intensive**	**Technology-Intensive**
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
N	2550	3720	6340
adj. R^2	0.375	0.453	0.545
p-value of inter-group difference test	Labor and capital 0.010	Labor and technology 0.000	Capital and technology 0.000

Notes: *, ** and *** are 10%, 5% and 1% significance level respectively. TI is manufacturing technology innovation, DF is Digital finance, ROA is return on assets, FA is fixed assets, CF is operating cash flow, Indd is proportion of independent directors, Tops is equity concentration, GDP is economic development level, and IS is industrial structure.

6. Conclusions and Policy Implications

6.1. Conclusions

In this study, the impact of DF on the technological innovation of manufacturing firms in China was examined using the fixed-effects and panel-threshold approaches. The goal was to determine if DF has been significant in improving the innovativeness of manufacturing firms, using China as a case study. The study identified gaps in the literature and used these approaches to produce new evidence and suggest policy implications to help improve the manufacturing and technology sector in China and the world at large. The study selected manufacturing companies listed in the Shanghai and Shenzhen A-share markets, using data from 2011 to 2020. After a series of tests, empirical findings that will help boost MTI were revealed, and the specific conclusions drawn are as follows: According to the study results, the benchmark regression results indicate that DF can promote technological innovation in manufacturing enterprises, and both coverage and depth of use have a significant positive impact. Also, the mechanism analysis indicates that DF can drive technological innovation in manufacturing enterprises by alleviating FCs. Moreover, the threshold-effect test indicates a dual-threshold effect based on market competition between DF and technological innovation. With the deepening of market competition, the promoting effect of DF on technology innovation weakens. Furthermore, the heterogeneity test analysis indicates that compared to the Eastern Region, DF is more effective in motivating the technological innovation of manufacturing enterprises in the Central and Western regions. Compared to state-owned enterprises, DF has a more significant promoting effect on technological innovation in non-state-owned manufacturing enterprises. From the perspective of factor-intensive types, DF can significantly promote technological innovation in labor-intensive and capital-intensive manufacturing enterprises but has no significant impact on the innovation level of technology-intensive enterprises. These findings provide great insights into DF and MTI studies and policy implementation for these firms, various industries, and countries.

6.2. Theoretical and Practical Implications

Based on the above conclusions, this article proposes the following theoretical and managerial implications and suggestions for the body of literature and policymakers.

First, the study makes significant contributions to the body of research. This contribution will assist future studies on DF and MTI. The use of the fixed-effects and panel-threshold approaches as a methodology for this kind of study is a great step toward applying relevant approaches to attain new evidence. These approaches have proven their effectiveness in predicting the impact of DF on MTI in this study. The major implication is that studies that share the same goals and objectives can apply this method and other models to investigate similar topics. Also, it can be of help in researching other industries that are yet to use them in their research. By adopting the methodology together with the variables, various findings can be established in the literature on DF and MTI, as well as other industries and research areas.

Second, practical implications are necessary for policymakers to help the promotion of MTI. Based on these findings, China must promote the construction of DF intensively and better empower manufacturing enterprises for technological innovation. Attention must be paid to improving the depth and digitization level of DF use and achieving the multi-dimensional and comprehensive development of DF. Manufacturing companies must be engaged in developing these initiatives to help them improve. Usually, policies are set forth without proper consultation with major stakeholders, which eventually hinders growth rather than improves it. As a result, improving the depth of digitalization in the sector through DF must be done in consultation with the manufacturing companies in question. This will result in a win-win situation for policymakers and enterprises.

Third, policymakers must take a critical look and focus on the innovation needs of manufacturing enterprises. By doing so, financial institutions should be encouraged to accelerate digital transformation; collect massive innovation elements with big data, Internet, and other technologies; achieve accurate demand docking and efficient resource matching; inject more credit resources for manufacturing enterprises; and solve financial difficulties. The success of DF is mostly dependent on these financial institutions, which lay the foundation for manufacturing firms or other industries to thrive. In that case, accelerating the digital transformation practices in correspondence with collecting massive innovation elements with big data, the Internet, and other technologies will help to achieve accurate demand docking and efficient resource matching. It will also help to establish strong security for these firms through the injection of more credit resources into manufacturing enterprises, to aid in solving financial difficulties in general. It is also important to expand the information contact surface of SMEs, guide the flow of resources to downstream enterprises and high-tech manufacturing industries, and enhance their innovation capabilities simultaneously.

Finally, policymakers must make it a priority to promote the balanced development of the regional manufacturing industry and achieve the better transformation and modernization of manufacturing firms. This can be achieved through the strengthening of regional horizontal integration. Also, manufacturing companies can be helped and promoted by reasonably guiding the transfer of the manufacturing industry based on the geographical and resource advantages of each region. Another aspect that can benefit the industry is to leverage the multiplier effect of manufacturing innovation. This has the potential to lift the face of manufacturing firms in transitioning from traditional operations to the digital and technological innovation age.

6.3. Limitations and Future Directions

Though this paper provides meaningful and relevant evidence and contributions, it also has some limitations that need to be exposed for future studies. First, the paper focuses on listed companies in sample selection, but due to the inability to obtain data on non-listed manufacturing companies, the sample range is limited. Also, limited data were used for listed companies (2011–2020). As a result, future studies can expand the sample size to include more updated data and samples of firms for new findings. It is necessary to collect more data and information about non-listed companies, understand their financing status and innovation needs, and inculcate them into new studies. Finally, the paper uses the fixed-effects model to study the relationship between DF and technology innovation for manufacturing firms in China. Although controlling variables at the enterprise and city levels are included, this cannot completely solve the endogeneity problems caused by missing variables. In the future, more factors related to technological innovation need to be considered. Also, future studies can apply the methodology or different methods and the idea in other countries and regions for new evidence since the study's results may have generalizability issues.

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