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The Impact of Digital Inclusive Finance on Corporate Innovation Output: Theoretical Mechanism and Empirical Test

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Abstract. This paper matches the data of Shanghai and Shenzhen A-share listed companies from 2011 to 2022 with the Peking University Prefecture-level Digital Inclusive Finance Index to investigate the impact of digital inclusive finance on corporate innovation output. Two-way fixed effects estimation shows that the development of digital inclusive finance significantly increases corporate invention patent applications and total patent applications. Mechanism tests show that digital inclusive finance is significantly correlated with the decline of financing constraints, while stronger financing constraints significantly inhibit corporate invention patent output, indicating that improved financing conditions are an important channel through which digital inclusive finance affects corporate innovation. Grouping results show that the promoting effect mainly appears in non-state-owned enterprises, non-private enterprises, cities with higher initial digital finance foundation and eastern regions. After replacing innovation indicators, performing winsorization, using the one-period lagged core explanatory variable and excluding financial industry samples, the main conclusions remain stable. The study indicates that digital inclusive finance can support corporate innovation by improving information identification and financing availability, but its effect depends on regional digital infrastructure and corporate financing structure.

Keywords: Digital inclusive finance, Corporate innovation, Invention patents, Financing constraints, Heterogeneity

1. Introduction

The accelerated integration of digital technology and financial services enables financial institutions to improve credit identification by using data from payment, transaction, tax payment and supply chains, and reduce the costs of information collection, risk assessment and service delivery [1]. Compared with the traditional credit model that mainly relies on collateral and financial statements, digital inclusive finance expands the coverage of financial services, and especially helps improve the financing availability of asset-light enterprises with insufficient information [2]. Meanwhile, corporate innovation features high input, long cycle, high risk and uncertain returns, and R&D activities are highly sensitive to sustained capital supply [3]. Therefore, whether digital inclusive

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finance can alleviate financing constraints and translate them into observable innovation outcomes is an important issue for evaluating the effectiveness of digital financial services serving the real economy.

This paper focuses on answering three questions: First, can the development of regional digital inclusive finance increase corporate invention patent applications and total patent applications? Second, do financing constraints constitute an important channel through which digital inclusive finance affects corporate innovation output? Third, does this impact vary with corporate ownership, private attribute, regional digital finance initial foundation and regional location? To this end, this paper matches the Peking University Digital Inclusive Finance Index with firm-year data of listed companies, and conducts baseline regression, mechanism test, heterogeneity analysis and robustness test after controlling for firm fixed effects and year fixed effects.

The main contributions of this paper are as follows: First, it examines the real economic consequences of digital inclusive finance from the perspective of corporate innovation output rather than mere financing scale. Second, it incorporates financing constraints into a unified analytical framework to identify the transmission relationship between digital finance improving financing conditions and innovation output. Third, it compares the estimation results of different enterprises and regions to provide empirical evidence for understanding the boundary conditions of the role of digital inclusive finance. It should be emphasized that the mechanism results in this paper are supportive evidence, and the difference in grouping significance is not equivalent to a significant difference in coefficients between groups. Follow-up studies still need to be further confirmed through interaction terms or inter-group coefficient tests.

From the perspective of empirical identification, this paper uses the changes in the level of digital inclusive finance in the regions where the same enterprise is located in different periods to identify its relationship with innovation output. It controls for time-invariant factors such as corporate culture, long-term governance characteristics and inherent innovation ability through firm fixed effects, and absorbs common shocks such as macroeconomic fluctuations, national financial policies and technological progress through year fixed effects. This setting cannot completely eliminate all endogeneity, but can significantly reduce the interference of unobservable firm heterogeneity on estimation results [4]. The rest of the paper is structured as follows: the second part constructs the theoretical mechanism of digital inclusive finance affecting corporate innovation and puts forward research hypotheses; the third part explains data sources, variable definitions and econometric models; the fourth part reports the results of baseline regression, financing constraint mechanism, heterogeneity and robustness; the fifth part summarizes the main findings, and puts forward policy implications and research limitations.

2. Theoretical analysis and research hypotheses

2.1. Digital inclusive finance and corporate innovation output

Traditional financial institutions usually value collateral assets, stable cash flow and historical credit records when granting credit, while innovation projects often lack collateralizable assets, and future returns are difficult to accurately evaluate. Information asymmetry and risk aversion will increase the cost of external financing, causing enterprises to reduce R&D projects or postpone innovation plans [5]. By integrating multi-dimensional operational data, improving risk control efficiency and reducing transaction costs, digital inclusive finance can expand credit coverage, enhance financing convenience and capital allocation efficiency [6]. With more stable financing supply, enterprises are more capable of maintaining R&D teams, purchasing R&D equipment and promoting technical

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experiments, and ultimately form innovation outcomes such as patent applications and grants. Accordingly, we propose:

The innovation-promoting effect of digital inclusive finance first comes from the improvement of the availability of financial services. Digital platforms break through the geographical restrictions of offline outlets, reduce the marginal cost of small-amount and high-frequency financial services, and enable financial institutions to grasp the operation and capital flow status of enterprises in a more timely manner [7]. For enterprises that lack traditional collateral but have stable transaction records, data elements can replace physical collateral to a certain extent, expanding their possibility of entering the formal financial system.

Second, digital inclusive finance may improve capital allocation efficiency. There are significant quality differences among innovation projects, while traditional financial institutions tend to adopt extensive credit granting methods when information is insufficient. Credit evaluation based on multi-dimensional data can improve the identification of enterprise operation quality and solvency, making financial resources more likely to flow to enterprises with higher productivity and stronger growth [8]. After the improvement of financing supply, enterprises can not only launch new R&D projects, but also be more capable of maintaining the continuity of existing projects, thereby increasing the probability of forming patent outcomes.

H1: The higher the development level of regional digital inclusive finance, the higher the corporate innovation output.

2.2. Financing constraint channel

Digital platforms can use payment flows, transaction relationships and operational behavior information to supplement traditional credit reporting data, alleviating information asymmetry between financial institutions and enterprises. Online application, automated approval and intelligent risk control can also reduce the time cost and institutional cost of financing [9, 10]. If digital inclusive finance indeed improves the external financing environment of enterprises, its development should reduce financing constraints; and the decline of financing constraints should improve the ability of enterprises to continuously carry out R&D and form innovation outcomes. Accordingly, we propose:

The key point of financing constraints affecting innovation is that R&D expenditures usually lack collateral assets that can be realized in the short term, and the sunk cost is high when the project fails. When the cost of external capital is significantly higher than the cost of internal capital, enterprises will give priority to meeting daily operations and debt repayment needs, and R&D expenditures are thus more likely to be compressed. Even if enterprises have good technological opportunities, they may fail to continuously advance projects due to cash flow fluctuations, insufficient credit lines or short loan maturities.

Digital inclusive finance can alleviate the above constraints through three paths: first, expanding the sources of credit information and reducing the risk of adverse selection; second, reducing the operating cost of a single loan by using automated approval and online services; third, carrying out post-loan monitoring with dynamic transaction data, reducing financial institutions' concerns about the risk uncertainty of innovative enterprises. If these mechanisms hold, the development of digital inclusive finance should first manifest as a decline in financing constraint indicators, and further correspond to an increase in corporate innovation output.

H2: Digital inclusive finance promotes corporate innovation output by alleviating corporate financing constraints.

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2.3. Enterprise and regional heterogeneity

There are significant differences in the ability of different enterprises to obtain traditional financial support, as well as in digital infrastructure, data resources and financial service supply in different regions, so the marginal effect of digital inclusive finance may not be consistent. Non-state-owned enterprises usually lack implicit guarantees, so digital finance may have a more obvious effect on improving their financing conditions; cities with higher initial digital finance foundation and eastern regions have more complete network facilities, platform ecosystems and market acceptance, which are also more conducive to the transformation of digital finance into innovation resources [11]. The grouping direction of private attribute depends on sample structure, governance characteristics and differences in financing channels, so it is not appropriate to make too strong a judgment in advance. Accordingly, we propose:

It should be pointed out that digital inclusive finance does not necessarily produce the largest marginal effect in regions with weak digital foundation. The effective operation of digital financial services requires the joint support of communication networks, data interfaces, credit information sharing mechanisms and financial institutions with digital capabilities. In regions with insufficient infrastructure or low data availability, even if the digital finance index increases, its actual impact on corporate financing decisions may be limited. Therefore, digital inclusive finance may present a complementary feature of "the more perfect the basic conditions, the more obvious the empowerment effect".

The heterogeneity of corporate ownership may also be complex. Non-state-owned enterprises usually face stronger credit rationing and thus may rely more on digital finance; but private enterprises and non-private enterprises are not completely equivalent, and the latter may also include foreign-funded enterprises and mixed-ownership enterprises. There are differences in information transparency, financing channels and innovation strategies among different organizational forms. Based on this, this paper reports the grouping results of ownership and private attribute separately, instead of treating them as the same classification in advance.

H3: The impact of digital inclusive finance on corporate innovation output varies with corporate ownership, private attribute and regional digital infrastructure.

3. Research design

3.1. Data sources and sample construction

This paper selects Shanghai and Shenzhen A-share listed companies from 2011 to 2022 as the research objects. The prefecture-level digital inclusive finance data comes from the Peking University Digital Inclusive Finance Index, corporate financial and governance data comes from the Wind Database, and patent application and grant data comes from the CSMAR Database. The digital inclusive finance index is matched according to the city code of enterprise registration place and year, and then the firm-level data is merged according to enterprise code and year. The baseline sample excludes ST and *ST enterprises and observations with missing core variables. The descriptive statistics sample includes 36,997 firm-year observations; after adding complete control variables, the baseline regression sample has 36,599 observations. The financial industry sample is further excluded in the robustness test.

Sample construction follows the following steps: first, take 2011, the starting year of the Peking University Digital Inclusive Finance Index, as the starting point of the sample period; second, match the prefecture-level digital inclusive finance index according to the city where the enterprise is

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registered and the fiscal year; third, merge corporate financial, governance, financing constraint and patent data according to securities code and year; finally, exclude financial industry enterprises, ST and *ST enterprises, and observations with missing core variables. Due to different degrees of missing variables, the maximum sample size for descriptive statistics is 36,997, while the effective regression sample including all baseline control variables is 36,599.

The advantage of using the listed company sample is that financial information and patent information are relatively standardized, which can construct a longer firm panel and control for firm fixed effects; its limitation is that listed companies are generally larger in scale and have more sufficient information disclosure, so the research conclusions are more applicable to enterprises in the formal capital market and cannot be directly extrapolated to a large number of unlisted small and medium-sized enterprises. Considering that the most important service objects of digital inclusive finance often include micro, small and medium-sized enterprises, this paper remains cautious about the external applicability of the estimation results.

3.2. Variable definitions

The explained variable is corporate innovation output. Baseline indicators include the natural logarithm of the number of invention patent applications plus 1 (ln_InventPatent) and the natural logarithm of the total number of patent applications plus 1 (ln_PatentTotal). Invention patents usually have higher requirements for technological novelty and inventiveness, so they are closer to substantive innovation; total patent applications can reflect the overall knowledge output of enterprises [12, 13]. The robustness test further uses the number of granted invention patents to reduce the measurement error caused by only submitting applications but not forming effective technical outcomes.

The core explanatory variable is the aggregate index of Peking University prefecture-level digital inclusive finance, which is divided by 100 to obtain DIF_index_100. This scaling only changes the numerical unit of the coefficient, and does not affect the significance and fitting results. Therefore, the regression coefficient represents the average change in the log indicator of corporate innovation output when the original digital inclusive finance index increases by 100 points. To avoid mechanically interpreting the log variable coefficient as a percentage change in the number of patents, this paper mainly uses "log-point change" and directional conclusions for expression.

The mechanism variable is financing constraints [14]. This paper mainly uses the absolute value of the SA index (AbsSA) to measure corporate financing constraints, and a larger value indicates stronger constraints [15]. The SA index is mainly constructed by firm size and age. Compared with indicators including cash flow or investment variables, it is less affected by the reverse impact of current operational decisions. The original design also considered the KZ index and WW index, but the existing core mechanism table is mainly based on AbsSA, so the expression of mechanism conclusions throughout the paper is based on the SA caliber.

Baseline control variables include firm size (Size), asset-liability ratio (Lev), return on total assets (ROA), proportion of independent directors (IndDirRatio) and board size (LnBoardSize). These variables control for enterprise resource base, debt pressure, profitability and governance structure respectively [16]. Descriptive statistics also report cash ratio, fixed asset ratio, growth, firm age and financial expense ratio to present the financial characteristics of sample enterprises.

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Table 1. Descriptive statistics of main variables

Variables	Observations	Mean	Std. Dev.	Min	Max
ln_InventPatent	36,997	1.3158	1.4587	0	9.0674
ln_PatentTotal	36,997	1.8365	1.7243	0	9.5772
ln_NonInventPatent	36,997	1.3285	1.5394	0	8.7013
ln_GrantInvent	36,997	0.8539	1.1523	0	8.2687
DIF_index_100	36,997	2.4347	0.7839	0.2126	3.6107
AbsSA	36,953	3.8143	0.3213	0.3707	5.7980
CashRatio	36,786	0.1908	0.1406	0	1.0000
Growth	34,068	0.1697	0.4591	-0.6830	2.9957
Age	36,953	2.0348	0.9564	0	3.4965

Note: Patent variables are all natural logarithms of the original number plus 1; AbsSA is the absolute value of the SA index.

Table 1 shows that the standard deviations of the log indicators of invention patents and total patents are both large, and the minimum value is 0, indicating that there are significant differences in innovation output among sample enterprises, and there are many enterprises with no patent applications in the current year. The mean value of the digital inclusive finance index divided by 100 is 2.4347, with a standard deviation of 0.7839, indicating that sample cities have sufficient cross-regional and inter-temporal variations in the level of digital finance development. The mean value of AbsSA is 3.8143, showing that listed companies still face financing constraints to varying degrees. Some financial variables have large ranges, so the following text tests whether the results are driven by extreme observations through two-sided winsorization.

3.3. Econometric model

The baseline model adopts a two-way fixed effects specification with firm fixed effects and year fixed effects:

$$Innovation_{it} = \alpha + \beta DIF_{ct} + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Where Innovation_it represents the innovation output of firm i in year t, DIF_ct represents the level of digital inclusive finance in city c where the firm is located in year t, X_it is the control variable, μ_i and λ_t are firm fixed effects and year fixed effects respectively. The core coefficient β measures the relationship between the development of digital inclusive finance and corporate innovation output.

Since the core explanatory variable changes at the city-year level and the explained variable changes at the firm-year level, the coefficient β mainly reflects the corresponding relationship between the change of digital inclusive finance level in the city where the same firm is located over time and the change of its innovation output. Firm fixed effects absorb long-term stable firm characteristics, and year fixed effects control for national common shocks. To avoid bias caused by omitted variables, the control variables all use firm-year financial and governance information.

The baseline model may still be affected by two types of endogeneity: first, local economic development, innovation policies or financial supply environment simultaneously promote digital finance and corporate innovation; second, regions with active innovation may in turn promote the

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expansion of digital financial services. This paper uses the one-period lagged core explanatory variable for robustness test to weaken contemporaneous reverse causality, but this method cannot completely replace strict exogenous shocks or instrumental variable identification. Therefore, this paper interprets the results as conditional correlations with strong robustness, and cautiously discusses the causal implications.

The mechanism test estimates the following two types of models in turn:

$$Constraint_it = \alpha_1 + \beta_1 DIF_ct + \gamma_1 \prime X_it + \mu_i + \lambda_t + \varepsilon_it$$

$$Innovation_it = \alpha_2 + \beta_2 DIF_ct + \delta Constraint_it + \gamma_2 \prime X_it + \mu_i + \lambda_t + \varepsilon_it$$

If β_1 is significantly negative, δ is significantly negative, and the coefficient of digital inclusive finance is still positive after adding financing constraints, it indicates that the financing constraint channel is supported. Heterogeneity analysis is grouped according to non-state-owned/state-owned, private/non-private, urban initial digital finance foundation level and eastern/central and western regions. Robustness checks include replacing the dependent variable, 1% and 99% two-sided winsorization, one-period lag of the core explanatory variable and excluding financial industry samples.

It should be noted that observing the change of the core coefficient after adding the financing constraint variable into the innovation equation is mechanism evidence rather than complete causal mediation analysis. Financing constraints and innovation may be affected by common unobserved factors, and the SA index itself is an indirect measure. Therefore, this paper comprehensively judges the transmission mechanism based on three aspects: the impact of digital inclusive finance on financing constraints, the impact of financing constraints on innovation, and the change of core coefficients.

4. Empirical results

4.1. Baseline regression

Table 2. Digital inclusive finance and corporate innovation output

Variables	(1) ln_InventPatent	(2) ln_PatentTotal
DIF_index_100	0.5039***(0.1316)	0.4478**(0.1821)
Size	0.1575***(0.0230)	0.1345***(0.0306)
Lev	-0.2097**(0.1032)	-0.2700**(0.1259)
ROA	-0.0198(0.0212)	-0.0261(0.0246)
IndDirRatio	0.2409**(0.1183)	0.4447***(0.1287)
LnBoardSize	-0.1693***(0.0594)	-0.2684***(0.0748)
Firm/Year fixed effects	Yes	Yes
Observations	36,599	36,599
R^2	0.1200	0.1283

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

Table 2 shows that the coefficients of the digital inclusive finance index on invention patent applications and total patent applications are 0.5039 and 0.4478, respectively, and are significant at

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the 1% and 5% levels, respectively. This means that after controlling for firm fixed effects, year fixed effects and firm characteristics, the improvement of regional digital inclusive finance level is significantly correlated with the increase of corporate innovation output. Since the core explanatory variable has been divided by 100, 0.5039 means that when the original index increases by 100 points, $\ln(1+\text{number of invention patent applications})$ increases by an average of 0.5039 log points. Considering that the dependent variable adopts the $\ln(1+y)$ form, especially in samples with zero patents, this coefficient should not be simply interpreted as a 50.39% increase in the number of patents.

From the perspective of different innovation indicators, the significance of digital inclusive finance on invention patents is higher than that on total patents, indicating that its effect is not only reflected in enterprises increasing low-threshold patent applications, but more likely related to innovation activities with higher technical content. The coefficient of firm size is significantly positive, indicating that enterprises with stronger resource base have higher innovation output; the asset-liability ratio is significantly negative, reflecting that higher debt pressure may squeeze R&D expenditures; the proportion of independent directors is positive while board size is negative, indicating that governance efficiency and supervision mechanisms may affect corporate innovation decisions. The ROA coefficient is not significant, indicating that short-term profitability is not the only factor explaining the innovation differences of sample enterprises.

Overall, the baseline regression supports H1. However, the digital inclusive finance index may simultaneously reflect regional information infrastructure, FinTech application and economic development level, so it is still necessary to judge whether this relationship conforms to the theoretical expectation of financing improvement combined with mechanism, heterogeneity and robustness results.

4.2. Financing constraint mechanism

Table 3. Test of financing constraint mechanism

Variables	(1) AbsSA	(2) ln_InventPatent	(3) ln_InventPatent
DIF_index_100	-0.1940***(0.0396)		0.3806***(0.1350)
AbsSA		-0.6376***(0.0657)	-0.6355***(0.0658)
Control variables	Yes	Yes	Yes
Firm/Year fixed effects	Yes	Yes	Yes
Observations	36,599	36,599	36,599
R^2	0.2125	0.1353	0.1354

Note: Control variables are consistent with Table 2; a larger AbsSA indicates stronger financing constraints.

In column (1), the coefficient of digital inclusive finance on AbsSA is -0.1940, which is significant at the 1% level. Since a larger AbsSA indicates stronger financing constraints, this result shows that the development of digital inclusive finance is significantly correlated with the decline of corporate financing constraints. Columns (2) and (3) show that the coefficient of AbsSA on invention patent output is about -0.64, indicating that the stronger the financing constraints, the fewer invention patent applications of enterprises. After adding financing constraints, the coefficient of digital inclusive finance is still 0.3806 and significantly positive, which is lower than 0.5039 in the baseline regression.

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The above results are consistent with the transmission logic of "digital inclusive finance — alleviation of financing constraints — improvement of innovation output". On the one hand, digital finance improves the financing availability of enterprises by expanding information sources and reducing service costs; on the other hand, improved financing conditions enable enterprises to bear the upfront investment of R&D projects and maintain long-term capital supply. The core explanatory variable coefficient is still significant after adding AbsSA, indicating that financing constraints are not the only channel, and digital inclusive finance may also affect corporate innovation by improving payment efficiency, promoting supply chain collaboration, broadening market information sources and improving risk management.

Therefore, the mechanism test provides support for H2, but the strict proportion of mediating effect cannot be drawn accordingly. In the future, if data on corporate loan interest rates, credit lines, loan terms or bank-firm matching can be obtained, it can more directly identify how digital finance changes corporate financing contracts, and further distinguish the channels of financing quantity, financing cost and financing term.

4.3. Heterogeneity analysis

Table 4. Heterogeneity analysis: core coefficient of digital inclusive finance

Grouping dimension	Group	Coefficient (Std. error)	Observations	R^2
Ownership	Non-state-owned enterprises	0.4655*** (0.1568)	32,755	0.0986
	State-owned enterprises	0.4773 (0.3346)	3,844	0.3514
Private attribute	Private enterprises	0.2506 (0.1815)	25,355	0.0925
	Non-private enterprises	0.5017** (0.2017)	9,729	0.1792
Initial digital finance foundation	Low	-0.2108 (0.2641)	12,557	0.2108
	High	0.7212*** (0.1772)	24,042	0.1411
Region	Eastern	0.7044*** (0.1971)	21,262	0.1566
	Central and western	0.1857 (0.2200)	15,337	0.1817

Note: All columns control for firm characteristics as well as firm and year fixed effects. Differences in significance within groups do not automatically imply significant differences in coefficients between groups.

Table 4 shows that the coefficient of digital inclusive finance is significantly positive in non-state-owned enterprises, non-private enterprises, cities with higher initial digital finance foundation and eastern regions, while it does not reach the common significance level in the corresponding control groups [17, 18]. The estimated coefficient of non-state-owned enterprises is 0.4655, indicating that enterprises without state-owned background may benefit more from digital credit identification and online financial services. When grouped by private attribute, significant results appear in non-private enterprises, suggesting that "non-state-owned" and "private" are not interchangeable classifications, and foreign-funded enterprises, collective enterprises and mixed-ownership enterprises may have different financing and innovation characteristics from typical private enterprises.

The regional grouping results are clearer: the estimated coefficient of cities with high initial digital finance foundation is 0.7212, and that of eastern regions is 0.7044, both significant at the 1% level; the coefficients of cities with low digital foundation and central and western regions are smaller and insignificant. This finding supports the complementarity between digital financial

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infrastructure and financial service capacity. The more complete the network coverage, data sharing, enterprise digital operation and technological capacity of financial institutions, the easier it is for digital inclusive finance to translate into real financing convenience and innovation support.

However, it cannot be asserted that the inter-group difference is statistically significant only based on "one group is significant and the other is not". A strict heterogeneity comparison should add the interaction term of digital inclusive finance and grouping variables in the full sample, and test the interaction coefficient. Therefore, Table 4 is more suitable as descriptive evidence of differentiated correlation patterns. The existing results partially support H3, and suggest that policy design should attach importance to both enterprise types and regional digital ecology.

4.4. Robustness checks

Table 5. Robustness checks

Test method	Core explanatory variable	Coefficient (Std. error)	Observations	R^2
Granted invention patents	DIF_index_100	0.3320*** (0.1277)	36,599	0.1067
Winsorization of continuous variables	DIF_index_100	0.4925*** (0.1306)	36,599	0.1182
One-period lag of core variable	L.DIF_index_100	0.3984*** (0.1247)	32,221	0.1236
Excluding financial industry	DIF_index_100	0.4971*** (0.1365)	35,529	0.1297
Total patent applications	DIF_index_100	0.4478** (0.1821)	36,599	0.1283

Note: All regressions include baseline control variables as well as firm and year fixed effects.

Table 5 shows that after replacing with granted invention patents, performing two-sided winsorization on continuous variables, using the one-period lagged digital inclusive finance index, excluding the financial industry, and switching to total patent applications, the core coefficients are all significantly positive, with values ranging from 0.3320 to 0.4971 [19]. The conclusion still holds after replacing with granted invention patents, indicating that the results are not completely driven by a large number of low-quality applications; the coefficient after winsorization is close to the baseline result, indicating that the impact of extreme values is limited; the lagged index is significantly positive, which takes into account the time required for innovation to form from financing improvement to outcomes, and alleviates contemporaneous reverse causality to a certain extent.

After excluding the financial industry sample, the coefficient of digital inclusive finance is still significantly positive, indicating that the conclusion is not caused by the digital operation characteristics of financial enterprises themselves. The results also remain consistent after switching to total patent applications, indicating that digital inclusive finance has a promoting effect on the overall knowledge output of enterprises. Overall, robustness checks improve the credibility of the baseline conclusion, but still cannot completely eliminate the problems of regional omitted variables and policy selectivity.

Follow-up studies can further construct quasi-natural experiments by using exogenous shocks such as urban digital infrastructure construction, mobile communication network expansion, digital finance pilots or internet popularization, and add city×year level economic, financial and innovation policy control variables. At the same time, Poisson pseudo-maximum likelihood models can be considered to deal with patent count variables and a large number of zero values, so as to test the robustness of the log-linear model specification.

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4.5. Further discussion

First, the role of digital inclusive finance in corporate innovation should be understood as the result of the interaction between changes in financial supply modes and corporate innovation demand. Digital technology reduces the cost of information collection and transaction processing, but only when enterprises themselves have real R&D opportunities, stable business activities and verifiable data records can financial institutions transform digital information into credit granting decisions. Therefore, digital inclusive finance does not unconditionally increase capital supply to all enterprises, but improves the ability of financial institutions to identify and serve enterprises that were originally difficult to cover. The higher significance of invention patents in the baseline results is also consistent with the logic that capital is more likely to flow to enterprises with clearer technical projects.

Second, digital inclusive finance is more likely to be a supplement to the traditional financial system rather than a simple substitute. Innovation projects usually require large amounts and long-term funds, and it is difficult to fully meet R&D needs only by relying on small-amount and short-term online loans. Digital platforms have advantages in credit identification, customer reach and post-loan monitoring, while commercial banks, guarantee institutions, venture capital and capital markets have more advantages in large-scale financing and risk sharing. Therefore, the key to improving innovation financing efficiency is to embed digital information capabilities into the credit granting process of traditional financial institutions, and form synergy between bank credit, sci-tech guarantee, intellectual property financing and equity capital.

Third, regional heterogeneity reveals the "basic condition constraint" of digital finance development. The larger coefficients of cities with higher initial digital finance foundation and eastern regions may not mean that weak regions do not need digital inclusive finance, but that the role of digital finance requires the joint support of network infrastructure, public data governance, enterprise digitalization and the technological capacity of financial institutions. If we only expand the number of online products but lack high-quality data and effective risk control, digital finance may stay at the level of payment convenience or short-term consumer credit, and it is difficult to translate into long-term support for enterprise R&D activities. Accordingly, the policy focus in weak regions should shift from single business expansion to infrastructure, data quality and institutional capacity building.

Fourth, while digital inclusive finance promotes innovation, it is also accompanied by new governance requirements. Algorithmic models may underestimate the credit quality of newly established enterprises, asset-light enterprises or emerging industries due to historical data bias; over-reliance on automated approval may also lead to maturity mismatch, duplicate credit granting and risk concentration. Policymakers need to maintain a balance between expanding financial coverage and maintaining financial stability, and establish mechanisms for data authorization, model review, appeal and error correction, and risk monitoring. For innovative enterprises, the goal of financial support should be to increase the possibility of high-quality projects obtaining long-term funds, rather than generally increasing leverage by lowering review standards.

Overall, the results of this paper support that digital inclusive finance has an innovation empowerment effect, but this effect has obvious conditionality: it depends not only on whether financial institutions can use digital information to improve credit allocation, but also on whether enterprises have the ability to absorb capital and form innovation outcomes. This understanding helps to avoid simply equating digital inclusive finance with the online migration of financial

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services, and provides direction for subsequent more detailed research from the perspectives of credit contracts, R&D cycles and innovation quality.

5. Conclusions, policy implications and research limitations

5.1. Main conclusions

Based on the data of Shanghai and Shenzhen A-share listed companies from 2011 to 2022, this paper investigates the relationship between the development of regional digital inclusive finance and corporate innovation output. The study finds that: First, digital inclusive finance significantly increases corporate invention patent applications and total patent applications, and the effect is more significant for invention patents. Second, digital inclusive finance is significantly correlated with the decline of corporate financing constraints, while financing constraints significantly inhibit invention patent output, and improved financing conditions are an important channel through which digital inclusive finance affects corporate innovation. Third, the promoting effect mainly appears in non-state-owned enterprises, non-private enterprises, cities with higher initial digital finance foundation and eastern regions, indicating that the role of digital finance is jointly affected by corporate financing structure and regional digital ecology. Fourth, various robustness checks support the basic conclusion that digital inclusive finance promotes corporate innovation output.

These findings indicate that digital inclusive finance not only has the functions of expanding payment coverage and improving residents' financial availability, but also can affect technological innovation in the real economy through the reconstruction of corporate credit information and the innovation of financing service modes. Meanwhile, when regional basic conditions are weak, the improvement of digital finance index may not be quickly translated into corporate innovation, which means that digital inclusive finance policies cannot be promoted independently of communication infrastructure, public data governance and local financial supply capacity.

5.2. Policy implications

First, improve digital financial infrastructure and credit information sharing mechanisms. We should continuously improve network coverage, data interfaces and digital government affairs levels in central and western regions and regions with weak digital foundation, and promote the standardized sharing of tax payment, social security, supply chain transactions and public credit information on the premise of law-based compliance, minimum necessity and protecting trade secrets, so as to reduce the cost of financial institutions in identifying the risks of innovative enterprises. Rather than simply pursuing the business scale of digital finance, we should pay more attention to data quality, risk control capacity and actual financing availability. Second, enhance differentiated financial support for innovative enterprises. Financial institutions can combine the characteristics of R&D projects such as long cycles, asset-light features and unstable cash flow to develop credit loans, intellectual property pledges, supply chain finance and medium and long-term R&D loans, so as to avoid evaluating long-term innovation projects with short-term operational indicators. The policy focus should be on enterprises with strong financing constraints but real R&D capabilities, rather than providing undifferentiated subsidies to all enterprises. Third, promote the synergy between digital finance policies and sci-tech innovation policies. Local governments can connect digital financial services with R&D subsidies, sci-tech guarantees, intellectual property protection and achievement transformation platforms to form a complete support chain from credit identification, capital supply to achievement transformation. At the same time, algorithm governance and data

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security supervision should be strengthened to prevent digital risk control from forming new information discrimination or excessive credit granting risks.

Fourth, improve the digital capacity of underdeveloped regions and small and medium-sized enterprises. The heterogeneity results show that regions with better digital foundation benefit more obviously, so policies should not only "provide digital finance", but also help enterprises form operational data that can be identified by digital finance. We can improve the data quality and financing application capacity of small and medium-sized enterprises through financial standardization, e-invoices, digital supply chains and enterprise management system training, so that digital inclusive finance can truly cover entities underserved by traditional financial services.

5.3. Research limitations

This paper still has several limitations. First, the number of patents can hardly fully reflect innovation quality, and there is a time lag from R&D input to patent application and grant. In the future, indicators such as citation times of invention patents, number of claims, patent maintenance years, patent value and new product sales revenue can be further used, and the differentiated impact of digital inclusive finance on innovation input, innovation efficiency and commercialization of achievements can be investigated. Second, the SA index is an indirect financing constraint indicator constructed based on firm size and age, making it difficult to observe loan interest rates, credit lines, maturity structure and guarantee methods. Follow-up studies can combine bank-firm loans, credit reporting or supply chain finance data to directly describe changes in financing contracts. Third, although firm and year fixed effects and various robustness checks reduce some endogeneity concerns, there may still be omitted variable bias caused by the co-variation of local policies, economic development and financial supply. Future research should use digital finance pilots, telecommunication infrastructure expansion or regulatory policy changes to construct stronger causal identification. Fourth, the information transparency and financing capacity of listed company samples are generally higher than those of unlisted small and medium-sized enterprises, so the extrapolation of research conclusions to small and micro enterprises needs to be verified by more micro data.

5.4. Research prospects

Future research can continue to advance from three aspects: identification strategy, mechanism data and innovation quality. First, in terms of identification strategy, policy shocks with clear temporal and regional differences such as digital finance pilots, telecommunication infrastructure upgrading, mobile payment access or local data governance reform can be used to construct difference-in-differences or event study models, and combined with pre-trend tests of policy implementation and placebo tests to enhance causal interpretation. If valid instrumental variables that only affect digital financial supply but do not directly affect corporate innovation can be found, the endogeneity caused by the simultaneous change of regional economic development and FinTech expansion can be further alleviated.

Second, in terms of mechanism data, enterprise innovation data should be matched with bank credit, supply chain finance, credit inquiry and intellectual property pledge data as much as possible to directly observe whether digital inclusive finance changes the probability of enterprises obtaining loans, loan interest rates, credit lines, collateral requirements and maturity structure. We can also distinguish whether the alleviation of financing constraints comes from new credit granting,

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reduction of financing cost, or better matching between loan maturities and R&D cycles, so as to more accurately explain the specific links of digital finance supporting innovation.

Third, in terms of innovation outcomes, patent quantity can be expanded to patent quality, innovation efficiency and economic performance. In addition to patent citations, claims and patent maintenance years, we can also investigate R&D input conversion rate, new product income, total factor productivity and the probability of enterprises entering new technology fields. Since innovation has obvious lag, follow-up studies should also set one-period, two-period and longer-term lag terms of digital inclusive finance to analyze the dynamic process of its impact from financing improvement to patent application, grant and industrialization.

Finally, research on unlisted micro, small and medium-sized enterprises should be expanded. Compared with listed companies, these enterprises lack public financial records and have fewer collateralizable assets. Theoretically, they are more likely to benefit from digital credit identification, but they are also more vulnerable to data deficiency, algorithm bias and short-term credit constraints. Combining tax, industry and commerce, e-invoice or platform transaction data can more comprehensively evaluate the inclusiveness of digital inclusive finance and test whether it truly narrows the innovation financing gap between enterprises of different sizes and regions.

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