Proceedings of ICEMGD 2026 Symposium: Rethinking Governance and Policy Innovation for Societal Challenges
DOI: 10.54254/2754-1169/2026.LH36030

Development of Digital Inclusive Finance and Debt Financing Costs of Small and Medium-Sized Enterprises: Micro Evidence from the Perspective of Information Asymmetry

Dawei Li

Financial Experimental Class, School of Finance, Shanghai University of Finance and Economics, Shanghai, China
13312130056@163.com

Abstract. Small and medium-sized enterprises (SMEs) often face problems such as incomplete credit information, insufficient mortgageable assets and high loan pricing in debt financing. Taking SMEs among China's A-share listed companies as the research sample, this paper matches the location of enterprises with the Peking University Digital Inclusive Finance Index on an annual basis, examines whether regional digital finance development changes the acquisition cost of corporate debt funds, and further analyzes the role of the external information environment in this process. Empirical results show that the higher the level of digital inclusive finance, the lower the debt financing cost of SMEs. Mechanism analysis indicates that digital finance can expand the availability of enterprise operation information, improve analyst coverage and information disclosure transparency, thereby reducing information friction between financial institutions and enterprises and lowering risk compensation requirements. Grouping tests find that this effect is more prominent in central and western regions and private enterprises. After further adopting the one-period lagged core explanatory variable, replacing financing cost indicators and adjusting the regional matching level, the main conclusions remain robust. From the perspective of corporate micro financing pricing, this paper provides empirical evidence that digital inclusive finance alleviates the financing pressure of SMEs.

Keywords: Digital Inclusive Finance, Debt Financing Cost, Small and Medium-Sized Enterprises, Information Asymmetry, Firm Fixed Effects

1. Introduction

SMEs play an important role in absorbing employment, promoting market competition and driving technology diffusion, and they also form a crucial foundation for the vitality of the real economy. However, in the process of external financing, such enterprises usually have a small scale and short operating history, with relatively limited public information and mortgage assets, making it difficult for financial institutions to accurately judge their actual risk level. To compensate for potential

DOI: 10.54254/2754-1169/2026.LH36030

losses caused by insufficient information, lending institutions often raise review requirements, add guarantee conditions or increase loan interest rates, leaving SMEs confronted with both insufficient financing availability and high financing prices at the same time [1].

The development of digital inclusive finance has provided new technical and institutional conditions for improving this situation [2]. Relying on mobile payment, online transactions, cloud computing and big data risk control, digital finance can convert scattered transaction records, tax information, supply chain exchanges and platform behavior data into credit evaluation materials. Compared with the traditional credit model that mainly relies on financial statements and collateral, digital tools reduce the costs of information collection, customer identification and post-loan monitoring, and also help financial institutions get closer to the actual operating status of enterprises.

Existing studies mainly discuss the impact of digital finance on entrepreneurial activities, financing demand, enterprise innovation, operating efficiency and financing constraints of SMEs [3-7]. However, whether digital finance directly affects the price of debt funds, and especially whether it can reduce financing premium by improving the information environment, still needs further testing. In addition, against different backgrounds of digital infrastructure, financial resource allocation and property rights systems, the role of digital inclusive finance may show obvious regional and enterprise-type differences. On this basis, this paper intends to answer three questions: first, whether the development of digital inclusive finance reduces the debt financing cost of SMEs; second, whether this effect is realized by alleviating information asymmetry; third, whether the relevant effects vary with regional location and enterprise ownership. The structure of the full paper is arranged as follows: the second part carries out theoretical analysis and puts forward hypotheses; the third part introduces data, variables and models; the fourth part reports empirical results; the fifth part gives conclusions and policy implications.

The possible marginal contributions of this paper are reflected in the following aspects. First, it focuses the research object on debt financing cost, a price-based financial indicator. Compared with simply observing financing constraints or loan availability, this indicator can better reflect the impact of digital finance on credit risk pricing. Second, it explains the mechanism of digital finance from the perspective of information asymmetry, and uses the number of analyst follow-ups and research reports to depict the external information environment of enterprises, so as to test whether the improvement of information transparency can reduce financing premium. Third, it further compares the estimation results of enterprises in different regions and with different property rights, revealing the differentiated performance of digital finance dividends in samples with different financial supply foundations and institutional backgrounds.

2. Theoretical analysis and research hypotheses

2.1. Definition of core concepts

Digital inclusive finance is a form of financial service formed by the combination of digital technology and the concept of inclusive finance. It emphasizes providing payment, credit, insurance, wealth management and other services to groups underserved by traditional financial services in a low-cost, wide-coverage and sustainable manner. In this paper, the Peking University Digital Inclusive Finance Index is used as a proxy variable for regional digital finance development. This index measures the regional digital finance level from dimensions such as coverage breadth, usage depth and digitalization degree, and can be matched annually with the place of registration or headquarters location of enterprises [8].

DOI: 10.54254/2754-1169/2026.LH36030

Debt financing cost is the comprehensive price paid by enterprises to obtain external debt funds, reflecting creditors' judgment on enterprises' credit risk, asset quality, debt repayment ability and future cash flow. From the perspective of financial statements, this cost usually manifests as explicit expenses such as interest expenses and financial expenses, and may also include implicit burdens such as guarantee requirements, approval cycles and additional clauses. This paper mainly uses the ratio of financial expenses to average interest-bearing liabilities to measure debt financing cost, and replaces it with other calibers in robustness tests.

2.2. Digital inclusive finance and financing cost

Digital inclusive finance may reduce the debt financing cost of enterprises through two links [2, 5]. First, in the information acquisition link, digital technology can integrate payment flows, tax records, supply chain transactions and platform operation data, enabling financial institutions to obtain richer basis for credit judgment, thereby reducing the risk premium added due to insufficient information. Second, in the financial service supply link, online approval and intelligent risk control reduce the costs of customer acquisition, due diligence and post-loan management, equipping financial institutions with the conditions to provide lower financing prices to SMEs. Accordingly, hypothesis H1 is proposed: the higher the development level of regional digital inclusive finance, the lower the debt financing cost of SMEs.

2.3. Information asymmetry channel

The key for digital finance to alleviate information asymmetry lies in "data-enhanced credit" and "improved risk control efficiency". The former refers to using alternative data such as payment, transaction, tax, social security and supply chain data to supplement traditional financial information, making the operating status of enterprises easier to verify and track by external entities; the latter uses algorithmic models, dynamic monitoring and high-frequency data processing to improve the efficiency of default risk identification, reducing information friction in the processes of pre-loan screening, credit pricing and post-loan supervision.

Under the traditional credit framework, SMEs often find it difficult to prove their actual risk level to financial institutions due to the lack of long-term credit records, standardized disclosure and sufficient collateral. Creditors such as banks can only make judgments based on limited financial statements, guarantee information and mortgage assets, which easily leads to conservative estimates or even misjudgments. The advantage of digital inclusive finance is that it converts information originally scattered in platform transactions, supply chain cooperation and public service systems into quantifiable credit signals, enabling continuous observation of enterprises' cash flow, performance records and operating stability. With richer information dimensions, the method of financing pricing may also gradually shift from "collateral or identity-led" to "operating data and cash flow-led".

After information asymmetry is alleviated, financing costs usually decline in two aspects. On the one hand, financial institutions can more accurately distinguish enterprises with different risk types, and reduce overly cautious pricing for low-risk enterprises; on the other hand, after the costs of pre-loan investigation and post-loan supervision decrease, enterprises are more likely to obtain financing arrangements with more appropriate terms, limits and interest rates. Based on the above analysis, hypothesis H2 is proposed: digital inclusive finance can reduce the financing cost of SMEs by lowering information asymmetry.

DOI: 10.54254/2754-1169/2026.LH36030

2.4. Regional and ownership heterogeneity

There are great differences in digital infrastructure, financial resource endowment and marketization degree among different regions in China. The traditional financial system in the eastern region is relatively complete, and digital finance is more reflected in the supplement and efficiency improvement of existing financial services; while the supply of financial services in the central and western regions is relatively insufficient, and SMEs are more likely to encounter financial exclusion. Therefore, digital inclusive finance may have a stronger gap-filling effect and marginal improvement role in these regions [5].

Enterprise ownership also changes the space for digital finance to play its role. State-owned enterprises usually have stronger implicit guarantees, more standardized information disclosure and more stable financing channels; private enterprises are more constrained by credit discrimination, insufficient collateral and low information transparency, and are more dependent on credit evaluation based on operating data and digital risk control [7]. Therefore, the reducing effect of digital inclusive finance on financing cost may be more obvious in the sample of private enterprises. Accordingly, hypothesis H3 is proposed: the cost-reducing effect of digital inclusive finance is heterogeneous among enterprises in different regions and with different ownership.

3. Research design

3.1. Data sources and sample construction

The data of this paper mainly includes three parts: the regional digital inclusive finance index, financial and governance data of listed companies, and variables depicting the external information environment. Among them, the digital inclusive finance index comes from the "China Digital Inclusive Finance Index" jointly compiled by the Institute of Digital Finance of Peking University and Ant Group [8]; enterprise-level data comes from the CSMAR Database, covering basic information, financial statements, audit information and analyst forecasts of listed companies.

The research sample is based on China's A-share listed companies, with an observation period from 2011 to 2023, on the basis of which SMEs are identified. Sample processing follows the following steps: excluding enterprises in the financial industry, deleting ST, *ST, PT and delisted companies, and removing observations with many missing core variables; at the industry-year level, enterprises with total assets or total market value in the bottom 50% are classified into the SME sample; continuous variables are winsorized at the 1% and 99% percentiles, and finally unbalanced panel data is formed.

3.2. Variable definition and measurement

The explained variable is corporate debt financing cost (FinCost). The benchmark indicator is measured by "financial expenses / average interest-bearing liabilities". Interest-bearing liabilities include short-term borrowings, non-current liabilities due within one year, long-term borrowings, bonds payable and long-term payables. If an enterprise's average interest-bearing liability is 0 in a certain year, the observation is not included in the financing cost calculation. The specific calculation method is shown in Equation (1).

$$\text{FinCost}_{it} = \text{Financial Expenses}_{it} / [(\text{Beginning Interest-Bearing Liabilities}_{it} + \text{Ending Interest-Bearing Liabilities}_{it})/2] \quad (1)$$

DOI: 10.54254/2754-1169/2026.LH36030

The core explanatory variable is the Digital Inclusive Finance Index (DIF). This paper adopts the total digital inclusive finance index at the prefecture-level city level, and matches it according to the city where the enterprise is registered. In regression, the index is processed by taking the natural logarithm or dividing by 100. The mechanism variable is information asymmetry (InfoAsym), which mainly uses the number of analyst tracking teams (ln_Analyst) and the number of analyst research reports (ln_Report) to measure the external information environment of enterprises; in the robustness discussion, audit fee (AuditFee) can also be used as an alternative indicator. Control variables include enterprise size (Size), asset-liability ratio (Lev), profitability (ROA), growth (Growth), cash holding level (Cash), asset tangibility (Tangibility) and enterprise age (Age).

Table 1. Variable definitions and measurement methods

Variable Category	Variable Symbol	Measurement Description
Explained variable	FinCost	The benchmark caliber is the ratio of financial expenses to average interest-bearing liabilities; in robustness tests, alternative indicators such as interest expenses / interest-bearing liabilities and financial expenses / total liabilities are used instead.
Core explanatory variable	DIF	Match the prefecture-level city digital inclusive finance total index according to the location of the enterprise, and enter the regression model after logarithmic or standardized processing.
Mechanism variable	ln_Analyst	Natural logarithm of the number of analyst tracking teams plus 1, used to reflect the market attention and external information coverage received by the enterprise.
Mechanism variable	ln_Report	Natural logarithm of the number of analyst research reports plus 1, used to measure information production and external supervision intensity.
Control variable	Size	Natural logarithm of total assets at the end of the period, used to control differences in enterprise scale, reputation capital and financing capacity.
Control variable	Lev	Total liabilities divided by total assets, used to control the leverage level and debt repayment risk of enterprises.
Control variable	ROA	Net profit divided by total assets, used to control enterprise profitability.
Control variable	Growth	Operating revenue growth rate, used to control enterprise growth.
Control variable	Cash	Monetary funds divided by total assets, used to control the internal liquidity of enterprises.

DOI: 10.54254/2754-1169/2026.LH36030

Table 1. (continued)

Control variable	Tangibility	Sum of fixed assets and inventory divided by total assets, used to depict the mortgageability of enterprise assets.
Control variable	Age	Natural logarithm of the difference between the current year and the establishment year plus 1, used to control the enterprise life cycle.

3.3. Econometric model specification

To estimate the average impact of digital inclusive finance on the debt financing cost of SMEs, this paper constructs a two-way fixed effects model of enterprise and year as shown in Equation (2):

$$FinCost_{i,t} = \alpha + \beta DIF_{r,t} + \gamma X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (2)$$

Where i denotes the enterprise, t denotes the year, and r denotes the region where the enterprise is located; $X_{i,t}$ is the enterprise-level control variable, μ_i is the enterprise fixed effect, λ_t is the year fixed effect, and $\varepsilon_{i,t}$ is the random disturbance term. To deal with the correlation of error terms within the same enterprise, standard errors are clustered at the enterprise level. The mechanism test is carried out in two steps [9]: first, use Equation (3) to test the impact of DIF on the proxy variable of information environment; second, use Equation (4) to incorporate the information environment variable into the financing cost equation, and observe the estimation changes of the core explanatory variable and the mechanism variable.

$$InfoAsym_{i,t} = \beta_0 + \beta_1 DIF_{r,t} + \Gamma X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (3)$$

$$FinCost_{i,t} = \gamma_0 + \gamma_1 DIF_{r,t} + \gamma_2 InfoAsym_{i,t} + \Gamma X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (4)$$

Heterogeneity analysis is grouped by region and enterprise ownership respectively. The regional dimension is divided into eastern region and central & western regions, and the property right dimension is divided into state-owned enterprises and private & other enterprises. Robustness tests mainly include three types of processing: lagging the core explanatory variable by one period, replacing the calculation caliber of financing cost, and adjusting the matching of digital finance index from prefecture-level city to provincial level.

4. Empirical results and analysis

4.1. Descriptive statistics

Table 2 presents the descriptive statistics of the main variables after winsorization. During the sample period, the average financing cost of SMEs is 0.0435, the median is 0.0356, and the maximum reaches 0.1890, indicating obvious differences in debt fund prices among enterprises. The average value of the prefecture-level city digital inclusive finance index is 5.4210, reflecting a certain degree of dispersion in the development level of digital finance in the sample regions. In terms of control variables, the median asset-liability ratio is 0.4025 and the average ROA is 0.0345, indicating that the overall financial structure and profitability of the sample enterprises are relatively stable. Correlation tests show that DIF_index is negatively correlated with financing cost, and the correlation coefficients among major control variables are all lower than 0.60, with relatively limited risk of multicollinearity.

DOI: 10.54254/2754-1169/2026.LH36030

It should be noted that the sample size of analyst tracking and research report variables is lower than that of financial variables, which indicates that not all SMEs can continuously receive attention from capital market intermediaries. This coverage difference itself also reflects the difference in the external information environment. If digital inclusive finance can increase analyst attention, its impact may come not only from the improvement of internal risk control efficiency of financial institutions, but also from the improvement of enterprise transparency through information production and external supervision of the capital market.

Table 2. Descriptive statistics of main variables

Variable Name	Symbol	N	Mean	Std. Dev.	Min	P25	Median	P75	Max
Financing cost	ln_FinCost	28,003	0.0435	0.0321	0.0012	0.0198	0.0356	0.0594	0.1890
Digital finance index	DIF_index	28,003	5.4210	0.3562	4.1205	5.2130	5.4890	5.6870	6.0125
Analyst tracking	ln_Analyst	17,105	1.8340	0.9850	0.0000	1.0986	1.9459	2.5649	3.8286
Analyst report	ln_Report	17,127	2.1240	1.1540	0.0000	1.3863	2.3026	3.0445	4.5420
Enterprise size	Size	28,003	21.054	0.9540	19.124	20.354	20.989	21.687	23.954
Asset-liability ratio	Lev	28,003	0.4125	0.1890	0.0520	0.2540	0.4025	0.5560	0.8950
Profitability	ROA	28,003	0.0345	0.0450	-0.154	0.0128	0.0321	0.0601	0.1687
Growth	Growth	28,003	0.1245	0.3120	-0.542	-0.054	0.0890	0.2450	1.6870
Enterprise age	Age	28,003	2.0543	0.6540	0.0000	1.6094	2.0794	2.5649	3.4657

4.2. Benchmark regression results

Table 3. Benchmark regression estimation results

Explanatory Variable	(1) ln_FinCost
DIF_index	-0.0743**(0.0364)
Size	-0.0260**(0.0112)
Lev	3.0215***(0.0610)
ROA	-0.7683***(0.1074)
Growth	0.0066(0.0140)
Age	0.0221(0.0141)
Firm fixed effects	Controlled
Year fixed effects	Controlled
Observations	28,003
R-squared	0.3343
Adjusted R-squared	0.3321

Notes: Robust standard errors clustered at the firm level are reported in parentheses; *, **, *and* *** denote significance at the 10%, 5%, and 1% levels, respectively.

DOI: 10.54254/2754-1169/2026.LH36030

Table 3 shows that the estimated coefficient of DIF_index is -0.0743, which is significant at the 5% level. This result indicates that after controlling for firm fixed effects, year fixed effects and enterprise-level characteristics, the higher the development degree of digital inclusive finance, the lower the debt financing cost of SMEs. In terms of control variables, the coefficient of enterprise size is negative and significant, indicating that larger enterprises usually have more mortgage resources and reputation capital, with relatively lower financing prices; the coefficient of asset-liability ratio is significantly positive, indicating that the increase of leverage level will increase the risk compensation required by creditors; the coefficient of ROA is significantly negative, indicating that enterprises with stronger profitability are more likely to obtain low-cost funds.

4.3. Mechanism test: information asymmetry channel

Table 4. Mechanism test of information environment

Explanatory Variable	(1) ln_Analyst	(2) ln_Report
DIF_index	0.0934**(0.0386)	0.1323***(0.0481)
Size	0.3839***(0.0112)	0.4786***(0.0140)
Lev	-0.4949***(0.0657)	-0.5593***(0.0825)
ROA	3.3846***(0.1719)	4.4856***(0.2231)
Growth	0.0426***(0.0144)	0.0901***(0.0194)
Age	-0.1796***(0.0151)	-0.2152***(0.0190)
Firm/Year fixed effects	Controlled	Controlled
Observations	17,105	17,127
R-squared	0.3023	0.3024
Adjusted R-squared	0.2985	0.2986

Notes: Robust standard errors clustered at the firm level are reported in parentheses; *, **, *and* *** denote significance at the 10%, 5%, and 1% levels, respectively.

The results in Table 4 show that the coefficient of DIF_index on the number of analyst tracking is 0.0934, significant at the 5% level; the coefficient on the number of analyst research reports is 0.1323, significant at the 1% level. It can be seen that there is a significant positive relationship between the development of digital inclusive finance and the improvement of the external information environment of enterprises, which can enhance the attention of information intermediaries to enterprises. After further incorporating the mechanism variables into the financing cost equation, the variables of analyst tracking and research reports show a negative impact on financing cost, while the absolute value of the DIF coefficient decreases but still maintains a certain degree of significance. This indicates that alleviating information asymmetry is one of the important transmission paths for digital finance to reduce financing costs.

DOI: 10.54254/2754-1169/2026.LH36030

4.4. Heterogeneity analysis

Table 5. Grouped regression: regional and ownership differences

Explanatory Variable	Eastern Region	Central & Western Regions	State-Owned Enterprises	Private & Others
DIF_index	-0.0587(0.0635)	-0.0797*(0.0451)	-0.0073(0.0486)	-0.1109**(0.0487)
Control variables	Controlled	Controlled	Controlled	Controlled
Firm fixed effects	Controlled	Controlled	Controlled	Controlled
Year fixed effects	Controlled	Controlled	Controlled	Controlled
Observations	9,696	17,598	14,024	13,979
R-squared	0.3758	0.3255	0.3371	0.3486
Adjusted R-squared	0.3701	0.3221	0.3327	0.3445

Notes: Robust standard errors clustered at the firm level are reported in parentheses; *, **, *and* *** denote significance at the 10%, 5%, and 1% levels, respectively.

The regional grouping results show that the coefficient of DIF_index in the central and western regions is -0.0797, significant at the 10% level; the coefficient in the eastern region is also negative, but fails to pass the conventional significance test. This indicates that in regions with relatively insufficient traditional financial services, digital finance is more likely to play a complementary role. The ownership grouping results show that the coefficient in the sample of private and other enterprises is -0.1109, significant at the 5% level; the coefficient in the sample of state-owned enterprises is close to zero and not significant. This result shows that credit evaluation based on operating data and quantitative models is more likely to alleviate the long-term non-market financing barriers faced by private enterprises.

4.5. Robustness tests

Table 6. Robustness test results

Explanatory Variable	One-period Lagged DIF	Replaced Financing Cost Caliber	Provincial Matching
L_DIF_index	-0.0753**(0.0373)		
DIF_index		-0.0749**(0.0355)	-0.1894*(0.1113)
Size	-0.0260**(0.0112)	-0.0286***(0.0109)	-0.0248**(0.0115)
Lev	3.0217***(0.0610)	0.9009***(0.0591)	3.0228***(0.0615)
ROA	-0.7692***(0.1075)	-1.3251***(0.1031)	-0.7592***(0.1076)
Growth	0.0067(0.0140)	0.0249*(0.0134)	0.0060(0.0139)

DOI: 10.54254/2754-1169/2026.LH36030

Table 6. (continued)

Age	0.0222(0.0141)	-0.0028(0.0138)	0.0210(0.0142)
Firm/Year fixed effects	Controlled	Controlled	Controlled
Observations	28,003	28,003	28,003
R-squared	0.3343	0.1517	0.3372
Adjusted R-squared	0.3321	0.1489	0.3343

Notes: Robust standard errors clustered at the firm level are reported in parentheses; *, **, *and* *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 6 shows that when the one-period lagged digital finance index is adopted, the core coefficient is -0.0753, significant at the 5% level, indicating that the benchmark conclusion is unlikely to be completely driven by synchronous relationship or reverse causality. After changing the measurement method of financing cost, the coefficient of DIF_index is -0.0749, still significant at the 5% level, indicating that the estimation results do not depend on a single caliber of the explained variable. After adjusting the digital finance index to provincial matching, the estimated coefficient is still negative and significant at the 10% level. Overall, the main conclusions have good robustness.

4.6. Endogeneity discussion

Although this paper controls for firm fixed effects, year fixed effects and multiple enterprise characteristics, the development of digital finance may still be related to unobservable factors such as regional economic foundation, industrial structure and financial resource allocation. For example, cities with higher economic development levels usually have both more complete digital infrastructure and lower financing prices. If such factors are not fully controlled, the estimation results may be affected by omitted variables. To alleviate this problem, this paper uses the one-period lagged DIF in robustness tests to reduce synchronous interference, and examines whether spatial measurement differences affect the conclusions through provincial matching.

Follow-up research can further improve the identification strategy. For example, historical communication facilities, early postal network foundations or the distance from cities to digital finance centers can be considered as instrumental variables, provided that these variables affect enterprise financing costs only through influencing the diffusion of digital finance. In addition, placebo tests, random rearrangement of digital finance indexes or construction of quasi-natural experiments can also be carried out to more strictly distinguish the effects of digital finance from other regional factors. The current results of this paper have been consistent in multiple tests, but there is still room for further expansion of stronger causal identification.

5. Conclusions and policy implications

Based on the sample of China's A-share SMEs, this paper analyzes the impact of digital inclusive finance on corporate debt financing costs and its transmission mechanism. The study finds that the improvement of regional digital inclusive finance level is significantly correlated with the decline of SME financing costs, and this remains valid after lagged term regression, replacement of financing cost caliber and adjustment of spatial matching level. Mechanism tests show that digital inclusive

DOI: 10.54254/2754-1169/2026.LH36030

finance can improve the external information environment of enterprises and alleviate information asymmetry between financial institutions and enterprises, thereby reducing the costs of credit search, screening and risk pricing. Heterogeneity analysis further shows that the cost-reducing effect is more obvious in the samples of central and western regions and private enterprises, indicating that digital finance has practical significance in improving the balance of regional financial services and optimizing the financing environment of private enterprises.

Based on the above conclusions, at the policy level, we should continue to improve the cross-departmental and wide-coverage digital public credit reporting system, promote the orderly sharing of tax, industry and commerce, judicial, social security and transaction data under the premise of compliance and security, and reduce the restriction of information islands on the credit evaluation of SMEs. At the same time, more investment in digital financial infrastructure should be directed to areas with weak traditional financial services to improve the communication network, digital terminals and data governance capabilities in the central and western regions. Financial institutions should also improve the digital risk control system on the basis of controllable risks, incorporate multi-dimensional operating data into the credit evaluation process, reduce excessive dependence on ownership identity and collateral, and improve the financing availability of private SMEs.

From a theoretical perspective, this paper shows that the function of digital inclusive finance is not only to expand the coverage of financial services, but also to reshape the processes of information production, risk identification and credit pricing. Digital technology can integrate scattered operating data into verifiable credit signals, making capital supply closer to the actual operating status of enterprises, thereby weakening the tendency of excessive reliance on collateral, property rights identity and regional financial resource endowment in traditional credit.

From a practical perspective, financial institutions can further optimize digital credit products, incorporate transaction flows, tax records, supply chain relationships and public credit data into the comprehensive evaluation framework, and design more matching credit limits, loan interest rates and repayment arrangements around the cash flow characteristics of private SMEs. Regulatory authorities need to simultaneously strengthen data security, algorithm transparency and consumer rights protection, to prevent digital finance from generating new risks such as data monopoly, privacy leakage or algorithmic discrimination while reducing information costs.

This paper still has certain limitations. Debt financing cost is jointly affected by accounting caliber, capital structure and the adjustment of enterprise financing behavior. Even with variable replacement, there may be measurement errors; information asymmetry is difficult to observe directly, and proxy variables such as analyst attention cannot fully cover its connotation; in terms of identification strategy, fixed effects and lagged terms can only alleviate part of the endogeneity problems. Future research can introduce more exclusive instrumental variables or quasi-natural experiments, and expand the sample to unlisted SMEs, so as to improve the causal explanatory power and external applicability of the conclusions.

References

[1] Kaplan, S. N., & Zingales, L. (1997). Do investment-cash flow sensitivities provide useful measures of financing constraints? *The Quarterly Journal of Economics, 112*(1), 169–215.

[2] Huang, Y. P., & Huang, Z. (2018). The development of digital finance in China: Present and future. *China Economic Quarterly, 17*(4), 1489–1502.

[3] Xie, X. L., Shen, Y., Zhang, H. X., et al. (2018). Can digital finance promote entrepreneurship? Evidence from China. *Economic Research Journal, 53*(10), 62–76.

[4] Tang, S., Wu, X. C., & Zhu, J. (2020). Digital finance and enterprise technological innovation: Structural characteristics, mechanism identification and effect differences under financial supervision. *Journal of*

DOI: 10.54254/2754-1169/2026.LH36030

Management World, 36(5), 52–66.

[5] Fu, Q. Z., & Huang, Y. P. (2018). Heterogeneous impact of digital finance on rural financial demand: Evidence from China household finance survey and Peking University digital inclusive finance index. *Economic Research Journal, 53*(11), 65–79.

[6] Song, M., Zhou, P., & Si, H. T. (2021). FinTech and enterprise total factor productivity: "Empowerment" or "disempowerment"? *China Industrial Economics*(4), 138–155.

[7] Sun, T., Li, W., & Zhang, L. (2019). Property rights nature, digital finance and financing constraints of small and medium-sized enterprises. *Journal of Financial Research*(6), 93–110.

[8] Guo, F., Wang, J. Y., Wang, F., et al. (2020). Measuring the development of digital inclusive finance in China: Index compilation and spatial characteristics. *China Economic Quarterly, 19*(4), 1401–1418.

[9] Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173–1182.