Proceedings of the 5th International Conference on Financial Technology and Business Analysis
DOI: 10.54254/2754-1169/2026.39166

Research on the Impact of Digital Finance Usage Depth on SME Financing Efficiency and Corporate Performance

Zeqi Wang

School of Economics, Anhui University, Hefei, China
i124304023.ahu@vip.163.com

Abstract. Small and medium-sized enterprises (SMEs) often struggle to obtain external funding. Digital finance has been proposed as one remedy. This paper asks whether the intensity with which such services are used translates into better access to finance, and what that implies for short-run accounting performance. The evidence comes from Chinese A-share firms on the SME Board and ChiNext, observed annually from 2011 to 2023, and is analyzed with a two-way fixed-effects specification. Three results stand out. First, an additional unit of usage depth accompanies a 0.0690-unit gain in financing efficiency, an estimate significant at the 5% level. Lagging the regressor by one year, or substituting the aggregate Digital Financial Inclusion Index, leaves both sign and significance intact. Second, financing efficiency and short-run return on assets move in opposite directions. The estimated coefficient is -0.1147, significant at the 1% level. One explanation is the interval between spending on research and development (R&D), capacity, and digitalization and the arrival of the associated payoffs. Third, the association is not uniform across firm sizes: it is stronger in the small-firm subsample (0.0118, significant at the 10% level) than among large firms (0.0026), yet the size interaction term is not significant. This paper treats financing efficiency as an outcome rather than a channel. Doing so gives a clearer reading of what digital finance does at the financing stage, and helps explain why efficiency gains and weaker short-run profitability can appear together.

Keywords: digital finance usage depth, financing efficiency, small and medium-sized enterprises, corporate performance, SA index

1. Introduction

The Central Financial Work Conference singled out five fields for priority attention in finance: technology, green, inclusive, pension, and digital. That decision signals where financial services are expected to contribute to the real economy. China counted 60 million small and medium-sized enterprises (SMEs) at the end of 2024, more than 90% of all registered enterprises. These firms supply over 60% of national tax receipts and gross domestic product (GDP). They are central to the economy and to society. Even so, their small size and opaque accounts keep financing out of reach for many. The evidence that such constraints hold SMEs back is extensive. As one study puts it, "digital finance can significantly alleviate the financing constraints of SMEs through enhancing TFP, improving internal control and mitigating agency problem" [1]. Firms usually operate better once

© 2026 The Authors. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).

DOI: 10.54254/2754-1169/2026.39166

constraints loosen. Digital finance has therefore drawn attention as a way out. According to the Digital Financial Inclusion Index (Peking University), the usage depth index for China climbed without interruption between 2011 and 2023. Its scope reaches across payment, credit lending, insurance, investment, and credit collection. Another account notes that "The digital finance usage depth index is composed of payment businesses, currency-based finance businesses, credit-lending businesses, insurance businesses, investment businesses, and credit collection" [2]. Digital financial services have since reached deeper into the real economy. Practice looks different, however. For most SMEs the services in use remain basic ones such as mobile payment; the use of credit, insurance, investment, and credit services remains low; and the potential of digital finance in more sophisticated business lines has yet to be realized. This raises two questions. Does more intensive use make it easier for SMEs to obtain finance? And how would any improvement show up in short-run accounting performance?

Two strands of work are relevant. The first asks how far digital finance loosens financing constraints. On the evidence assembled so far, "the development of digital finance can significantly reduce the cost of corporate debt financing" [3]. That finding is not universal. A second strand reports a different result: "The inhibitory effect of the depth of digital finance utilization on debt financing costs has not been fully realized" [4]. The outcome, then, depends on which financing instrument is examined. On the channel behind lower costs, the literature notes the following: "digital finance reduces information asymmetry through online platforms and big data analysis, assisting enterprises in accurately assessing market conditions and financing needs, thereby better matching investors and fundraisers, improving liquidity, and reducing financing time and costs" [5].

The second group turns directly to financing efficiency and firm performance. Published estimates point to the same conclusion: "higher ESG performance and digital finance enhance corporate financing efficiency at the 1% significance level" [6]. Elsewhere the argument runs: "digital inclusive finance uses digital technology to alleviate financing constraints and improve the credit supply, which in turn increases firm value", with the effect concentrated among smaller and privately held firms [7]. In much of this work, financing efficiency or financing constraints appear as an intervening variable rather than as the object of interest. Other firm-level outcomes are shaped through the financing channel as well. Work on digitalization is explicit: "Improving enterprise financing is an important mechanism through which digital finance facilitates firms' digital transformation", and reports larger effects for small and non-state-owned firms [8]. For digital technology innovation, published results show that "Compared with the coverage of digital finance, the promotion effect of the depth of digital finance on digital technology innovation is more prominent" [9]. A further strand treats financing constraints and production efficiency as routes from digital finance to corporate environmental performance: "by directly alleviating financing constraints, digital finance enhances a firm's capacity to invest in advanced clean production technologies and sustainable management practices" [10]. Usage depth has been studied in its own right as well. One study decomposes the index and concludes that "digital finance restrains corporate tax avoidance such that depth of use is dominant while coverage breadth and digitalization are secondary" [11].

Two questions remain largely untouched. First, financing constraints and financing efficiency usually enter the analysis as mechanisms rather than as outcomes, even though they are the first point at which digital finance touches the firm. Second, the assumption that better financing efficiency must improve performance is seldom tested, and the interval between committing capital and receiving a return draws little attention. This paper therefore asks whether more intensive use of

DOI: 10.54254/2754-1169/2026.39166

digital finance lifts SME financing efficiency, and whether any such rise shows up in return on assets (ROA) in the short run.

Making financing efficiency the outcome rather than a link in the chain lets this study speak more directly to what digital finance does at the financing stage. Whether better financing efficiency leads to better short-run performance is tested rather than assumed. The results explain how financing efficiency and short-term return on assets can move in opposite directions. They also give SME managers a basis for deciding how to deploy new funds, and provide evidence for policies aimed at SMEs' financing needs.

2. Data sources, variables, and empirical strategy

2.1. Sample selection and data sources

Firms on China's A-share SME Board and ChiNext, observed from 2011 to 2023, make up the initial sample. The SME Board ceased to exist as a separate segment in April 2021, when the Shenzhen Stock Exchange folded it into the Main Board. Firms that had been on the SME Board before that change are therefore retained, and their annual records are tracked to 2023. Their size is close to that of SMEs, so they suit the question at hand. Screening follows Zhou and Ji [12]: financial firms are dropped, along with firms carrying ST or *ST status and observations with missing core variables. Winsorization at the 1st and 99th percentiles is applied to all continuous variables.

Two kinds of data are combined. The China Stock Market & Accounting Research (CSMAR) database supplies the accounting and governance variables for individual firms. The digital finance measures come from the index published by Peking University's Institute of Digital Finance. Usage depth is recorded at the prefecture level, and each firm is linked to the value for the city where it is registered. Xu et al. and Li and Xie take the same approach [7, 8].

2.2. Variable definitions

(1) Core dependent variable: financing efficiency (FE)

The main dependent variable is SME financing efficiency. It refers to how quickly and cheaply a firm can secure the funds it needs, and how well it then uses them. It is proxied by an inverse indicator of financing constraints.

The size-age (SA) index is a standard tool in corporate finance, and financing efficiency is defined as the negative of its absolute value: $\mathrm{FE} = -|\mathrm{SA}|$. The SA index carries a negative sign, and a larger absolute value corresponds to tighter constraints. A larger FE therefore signals constraints that bind less and efficiency that is higher. Because it uses only size and age, the SA index is less exposed to endogeneity than measures built on financial variables; those variables may be endogenous themselves.

$$SA = -0.737 \times Size + 0.043 \times Size^2 - 0.04 \times Age \quad (1)$$

In this expression, Size is the log of total assets and Age records how long the firm has been in existence. Other authors have used the SA index to measure the constraints firms face. Fan et al. write, "SA index is used to measure financial constraints (FC1) according to Hadlock and Pierce", and Han et al. write, "we calculate the financing constraints index (FC) of firms by following Hadlock & Pierce" [13, 14]. This study applies the same construction.

(2) Additional dependent variable: return on assets (ROA)

DOI: 10.54254/2754-1169/2026.39166

The analysis then turns to whether financing efficiency bears on corporate accounting performance. As in Xu et al. [7], performance is captured by return on assets (ROA), net profit scaled by total assets. ROA shows earnings relative to the assets a firm holds.

(3) Core explanatory variable: digital finance usage depth (Depth)

The proxy for digital finance is Peking University's Digital Financial Inclusion Index, which has three components: coverage breadth, usage depth, and the degree of digitalization. As in Tang and Geng, the raw figure is divided by 100 [3]. Earlier subdimension results show that usage depth carries the most information, so the usage-depth subindex (Depth) is the principal regressor [10, 11]. It measures how intensively digital financial services are taken up in the real economy.

(4) Control variables

The covariates are those used by Zhou and Ji and Fan et al. [12, 13]: the logs of firm size (Size) and board size (Board); Age, the log number of years since the firm was established; leverage (Lev); revenue growth (Growth); ownership concentration (Top1); and a dummy (Dual) for chief executive officer (CEO) duality, equal to one when a single person holds both the chair and the general-manager posts and 0 otherwise.

2.3. Model specification

The specification below, with fixed effects for firm and year, tests what usage depth does to the financing efficiency of SMEs:

$$FE_{i,t} = a_0 + a_1 \mathrm{Depth}_{c,t} + a_2 \mathrm{Controls}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{2}$$

Here i runs over firms and t over years. $FE_{i,t}$ is the financing efficiency of firm i in year t; $Depth_{e,t}$ is the depth of digital finance use in the firm's city of registration; Controls $_{i,t}$ is the set of covariates; μ_i and λ_t are the firm and year fixed effects; and $\varepsilon_{i,t}$ is the error term, with standard errors clustered by firm. A positive and significant a_1 would mean the two move together.

The next specification tests the performance effect that follows an improvement in financing efficiency:

$$\mathrm{ROA}_{i,t} = \beta_0 + \beta_1 FE_{i,t} + \beta_2 \mathrm{Controls}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{3}$$

This equation relates financing efficiency to ROA. The covariates and fixed effects are the same as in Model (1), and β_1 summarizes the conditional link between FE and ROA. A negative and significant β_1 would mean that firms with higher financing efficiency earn less on their assets in the short run.

The baseline is a panel regression with firm and year fixed effects. These absorb heterogeneity that does not change over time and trends common to the sample. Two robustness exercises are run: the main regressor is lagged one period, and usage depth is swapped for the aggregate Digital Financial Inclusion Index. Endogeneity is handled by two-stage least squares (2SLS), with an instrument formed from a time trend multiplied by the great-circle distance separating a firm's registered city from Hangzhou. Size heterogeneity is examined by splitting the sample at the annual median of Size and adding an interaction with a large-firm dummy.

DOI: 10.54254/2754-1169/2026.39166

2.4. Summary statistics

Table 1 summarizes the variables. For FE the average is -4.079 and the standard deviation 1.144, so firms differ widely on this measure. Depth averages 2.467, with standard deviation 0.791, which shows that cities are not alike in their use of digital finance. ROA averages 0.035, with standard deviation 0.076. Size, Lev, and Top1 average 21.724, 0.365, and 32.093%, respectively. The other variables look much as the sample construction and the winsorization imply.

Table 1. Summary statistics

	Obs.	Mean	Standard deviation	Minimum	Median	Maximum
ROA	19842	0.035	0.076	-0.341	0.042	0.205
FE	19842	-4.079	1.144	-7.632	-3.930	-2.036
Depth	3330	2.467	0.791	0.140	2.862	3.500
Distance × trend (IV)	3487	5766.372	4817.339	0	4458.184	14489.097
Size	19842	21.724	0.989	19.815	21.630	24.595
Age	26777	4.544	2.750	0	6.103	6.823
Lev	19842	0.365	0.193	0.045	0.346	0.884
Growth	17903	0.165	0.367	-0.569	0.113	1.999
Top1	19907	32.093	13.781	8.380	30	69.960
Board	19840	2.082	0.187	1.609	2.197	2.485
Dual	19842	0.380	0.485	0	0	1
|SA|	19842	4.086	1.188	0.707	3.930	11.731

3. Empirical findings

3.1. Correlation patterns

Figure 1 presents the Table 2 correlations as a heatmap. Depth and FE are negatively related (-0.326). FE comes from the SA index, and that index is largely a function of size; the bivariate pattern is therefore mostly a product of how the measure is built. The FE-Size correlation is -0.999 and the Depth-Size correlation 0.330. This says more about the definition of FE than about any harmful effect of digital finance. Once controls enter, the estimated coefficient on Depth becomes positive (Table 3). Apart from the mechanical FE-Size link, no pairwise correlation exceeds 0.8 in absolute value.

Table 2. Pairwise correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	FE	Depth	Distance × trend (IV)	Size	Age	Lev	Top1	Board	Dual
FE	1								
Depth	-0.326***	1							
Distance × trend (IV)	-0.325***	0.487***	1						
Size	-0.999***	0.330***	0.327***	1					
Age	0.0387***	-0.0374*	-0.0595***	-0.0151*	1				

DOI: 10.54254/2754-1169/2026.39166

Table 2. (continued)

Lev	-0.457***	0.227***	0.154***	0.457***	-0.0203**	1			
Top1	0.0404***	-0.256***	-0.183***	-0.0448***	-0.0161*	-0.0637***	1		
Board	-0.138***	-0.119***	-0.0727***	0.141***	0.0387***	0.0580***	-0.0374***	1	
Dual	0.102***	-0.0143	-0.00653	-0.103***	-0.00381	-0.0714***	0.0406***	-0.135***	1

Note: FE equals minus the absolute SA index, and that index is essentially a function of size and age. The -0.999 reading between FE and Size is therefore a feature of the measure rather than a finding. Multiplying 0.330 (Depth with Size) by -0.999 gives about -0.330, close to the -0.326 between Depth and FE, so the negative sign travels through size rather than originating in digital finance. Once size and the other covariates are held constant, Depth enters positively (Table 3). Firm-clustered std. errors in parentheses; ***/**/*: 1%/5%/10%.

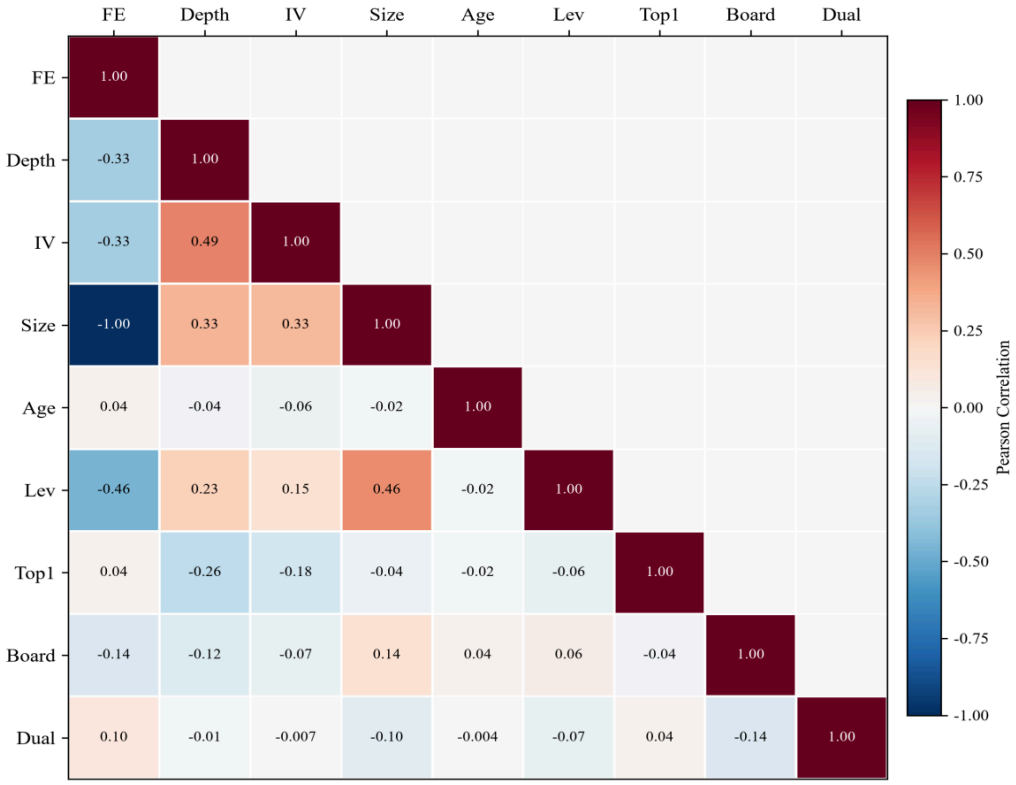


Figure 1. Correlation heatmap

3.2. Baseline regression analysis

Table 3 reports the baseline estimates. The Depth coefficient is 0.4716 and insignificant when nothing is controlled for. With all controls included, it drops to 0.0690, which is significant at the 5% level. Holding size, age, leverage, and the other covariates fixed, an extra unit of Depth corresponds to 0.0690 more units of FE. Since FE equals -|SA|, this implies constraints that bind less tightly.

Size has a coefficient of -1.1445, significant at the 1% level. The negative value calls for caution: size is an ingredient of the SA index and therefore of FE. Model (2)'s adjusted R^2 is 0.9988.

DOI: 10.54254/2754-1169/2026.39166

Table 3. Baseline estimates for usage depth and financing efficiency

	(1)	(2)
	Model (1)	Model (2)
Depth	0.4716	0.0690**
	(0.3067)	(0.0275)
Size		-1.1445***
		(0.0060)
Age		0.6400
		(0.8763)
Lev		0.0123
		(0.0163)
Top1		0.0001
		(0.0003)
Board		0.0074
		(0.0129)
Dual		0.0026
		(0.0035)
Constant	-5.1971***	16.6379***
	(0.7574)	(5.4127)
Observations	3314	3314
Adjusted R^2	0.8317	0.9988

Note: Firm-clustered std. errors in parentheses; ***/**/*: 1%/5%/10%.

3.3. Robustness checks

Table 4 reports two checks on the baseline result.

Table 4. Robustness of the baseline estimate

	(1)	(2)	(3)
	Baseline	Lagged explanatory variable	Alternative total index
Depth	0.0690**		
	(0.0275)		
Size	-1.1445***	-1.1514***	-1.1448***
	(0.0060)	(0.0061)	(0.0060)
Age	0.6400	0.4348	0.6638
	(0.8763)	(0.8823)	(0.8745)
Lev	0.0123	0.0249*	0.0117
	(0.0163)	(0.0144)	(0.0163)
Top1	0.0001	0.0002	0.0001
	(0.0003)	(0.0003)	(0.0003)
Board	0.0074	0.0083	0.0069
	(0.0129)	(0.0114)	(0.0129)
Dual	0.0026	0.0040	0.0028

DOI: 10.54254/2754-1169/2026.39166

Table 4. (continued)

	(0.0035)	(0.0032)	(0.0035)
L.Depth		0.0700***	
		(0.0257)	
DF_total			0.1203***
			(0.0455)
Constant	16.6379***	18.0495***	16.3624***
	(5.4127)	(5.4510)	(5.4178)
Observations	3314	3004	3314
Adjusted R^2	0.9988	0.9990	0.9988

Note: Firm-clustered std. errors in parentheses; ***/**/*: 1%/5%/10%.

(1) Lagged explanatory variable. Lagging Depth by one period allows for effects that take time to appear and eases concerns about reverse causality. L.Depth has a coefficient of 0.0700, significant at the 1% level; both its sign and its size are close to the baseline value of 0.0690, which points to a durable positive association.

(2) Alternative explanatory variable. When the aggregate Digital Financial Inclusion Index (DF_total) takes the place of Depth, the coefficient is 0.1203, significant at the 1% level. It is positive and close to the baseline, so the finding does not hinge on the usage-depth measure.

3.4. Endogeneity treatment

Both the baseline regression and the robustness exercises point to a positive role for usage depth in financing efficiency. Reverse causality and omitted variables remain possibilities, however. The interaction between a time trend and the spherical distance from a firm's registered location to Hangzhou is therefore used as an instrument in a 2SLS estimation. Table 5 reports the results. Hangzhou hosts the headquarters of Ant Group and ranks among China's leading centers of digital finance. Activity in the field radiates outward from the city, so the further away a firm is registered, the less developed local digital finance tends to be. Distance of this kind is a historical given and can be treated as exogenous; it has no direct bearing on the financing efficiency of an individual firm. Distance on its own does not move over time and would be absorbed by the firm fixed effects, so it is interacted with a time trend to introduce variation across years. Relevance is not in doubt. The instrument enters the first stage with a negative coefficient (t = -13.63), significant at the 1% level, and the F statistic for the excluded instrument, 185.82, sits far above the customary cut-off of 10, so weak identification is unlikely. At the second stage Depth has a coefficient of 0.3089 (t = 3.06, p = 0.002), significant at the 1% level, which retains the positive sign seen in the baseline.

Table 5. Instrumental-variable estimates (2SLS)

	(1)
	Second stage
Depth	0.3089***
	(0.1011)
Size	-1.1431***
	(0.0060)
Age	0.3481

DOI: 10.54254/2754-1169/2026.39166

Table 5. (continued)

	(0.8726)
Lev	0.0102
	(0.0165)
Top1	0
	(0.0004)
Board	0.0093
	(0.0135)
Dual	0.0042
	(0.0038)
Observations	3314

Note: The instrument multiplies a time trend by the great-circle distance (km) from the firm's registered location to Hangzhou. Firm-clustered std. errors in parentheses; ***/**/*: 1%/5%/10%.

3.5. Effect of financing efficiency on corporate performance

Taken together, the preceding results indicate that deeper use of digital finance goes together with higher financing efficiency among SMEs. The next question is whether financing efficiency bears on corporate accounting performance. Looser financing constraints may support production and lift profitability. The same funds may also be channeled into capacity and research and development (R&D), which weighs on profit in the near term. Model (2) accordingly regresses ROA on FE. Table 6 presents the results.

Table 6. Financing efficiency and corporate ROA

	(1)	(2)
	Model (1)	Model (2)
FE	-0.0204***	-0.1147***
	(0.0044)	(0.0409)
Size		-0.1063**
		(0.0471)
Age		-0.8654
		(0.7315)
Lev		-0.1465***
		(0.0216)
Top1		0.0014***
		(0.0004)
Board		0.0199
		(0.0151)
Dual		0.0141***
		(0.0050)

DOI: 10.54254/2754-1169/2026.39166

Table 6. (continued)

Constant	-0.0471***	7.1829
	(0.0178)	(4.6117)
Observations	3314	3314
Adjusted R^2	0.3530	0.3991

Note: The dependent variable is ROA and the regressor is financing efficiency ($FE = -|SA|$, minus the absolute SA index). Firm-clustered std. errors in parentheses; ***/**/*: 1%/5%/10%.

FE enters Model (1) with a coefficient of -0.0204, significant at the 1% level. Introducing the controls in Model (2) changes it to -0.1147, which remains significant at the 1% level. Both specifications rest on 3,314 firm-year observations. In the fully specified model, one more unit of FE is matched by a fall of 0.1147 units in ROA. That amounts to a negative short-run link between financing efficiency and accounting performance.

Table 6 takes ROA as its dependent variable. Firm and year effects strip out persistent cross-firm differences and shocks shared by all firms in a given year. Adjusted R^2 falls in the 0.35–0.40 range, which is ordinary for firm-level panels.

Three channels could account for the negative short-run link. Firms may put the extra external finance into R&D, capacity, and digitalization, where payoffs arrive only after a lag. Lighter financing pressure may also let managers favor long-term growth over current earnings, lifting spending on innovation and on opening up markets. Finally, using digital financial services is not free: the associated charges depress profit for a time. Taken together, these channels imply that financing gains and the timing of returns should be weighed together, by managers and by policymakers alike.

3.6. Heterogeneity analysis

Table 7 asks whether the link between Depth and FE depends on how large a firm is. Firms are sorted at the annual median of Size. Both subsamples carry firm and year effects. Small firms have a Depth coefficient of 0.0118, significant at the 10% level; the large-firm figure of 0.0026 is not significant. The small-firm estimate is roughly 4.5 times the large-firm one, yet the interaction coefficient reported in Table 7-b is not significant. The pattern therefore hints at a stronger association among small firms without establishing that the two groups differ in a statistically meaningful way.

Table 7-a. Subsample estimates by firm size

	(1)	(2)
	Large firms	Small firms
Depth	0.0026	0.0118*
	(0.0274)	(0.0069)
Size	-1.2265***	-1.0589***
	(0.0063)	(0.0021)
Age	1.5060	0.3710

DOI: 10.54254/2754-1169/2026.39166

Table 7-a. (continued)

	(1.0090)	(0.2525)
Lev	0.0248	-0.0062
	(0.0157)	(0.0056)
Top1	0.0003	-0.0002
	(0.0003)	(0.0001)
Board	0.0168	0.0080*
	(0.0103)	(0.0048)
Dual	0.0075**	-0.0009
	(0.0036)	(0.0013)
Constant	13.2734**	16.6513***
	(6.2191)	(1.5668)
Observations	1599	1672
Adjusted R^2	0.9994	0.9997

Note: Both subsamples include firm and year effects and the firm-level covariates. Firm-clustered std. errors in parentheses; ***/**/*: 1%/5%/10%.

Table 7-b. Size interaction test

	Full sample
Depth	0.0695**
	(0.0275)
Depth × Large	-0.0023
	(0.0022)
Size	-1.1419***
	(0.0080)
Age	0.6254
	(0.8775)
Lev	0.0129
	(0.0163)
Top1	0.0001
	(0.0003)
Board	0.0075
	(0.0129)
Dual	0.0026
	(0.0035)
Constant	16.6719***
	(5.4118)
Observations	3314
Adjusted R^2	0.9988

DOI: 10.54254/2754-1169/2026.39166

Note: Depth × Large multiplies usage depth by the large-firm dummy; its insignificance means the gap between the two size groups cannot be called statistically significant. Firm-clustered std. errors in parentheses; ***/**/*: 1%/5%/10%.

4. Conclusions and implications

4.1. Main conclusions

Drawing on Chinese A-share firms on the SME Board and ChiNext over 2011–2023, this paper applies a two-way fixed-effects model to trace how digital finance usage depth relates to SME financing efficiency and how financing efficiency in turn relates to corporate performance. Three points stand out.

First, where digital finance is used more intensively, constraints are looser and financing efficiency higher. The baseline figure is 0.0690, significant at the 5% level. With Depth lagged one period it becomes 0.0700; with the aggregate Digital Financial Inclusion Index in its place, 0.1203. Both are significant at the 1% level.

Second, the two variables move in opposite directions in the short run: higher financing efficiency comes with lower accounting profitability. The ROA regression returns a coefficient on FE of -0.1147, significant at the 1% level. One reading is that the funds released are committed to R&D, capacity, and digitalization, with payoffs that arrive only later. The timing of those returns is therefore something managers and policymakers should weigh when they assess what improved financing access does to performance.

Third, the positive link between usage depth and financing efficiency appears tighter for smaller firms: 0.0118, significant at the 10% level, against 0.0026 for larger ones, which is insignificant. The size interaction is insignificant as well. The evidence points towards a larger benefit for smaller firms, but does not establish one.

4.2. Policy recommendations

Three policy implications follow.

First, both the depth and the breadth of digital financial services need to grow. That requires better infrastructure and the responsible use of artificial intelligence, big data, and cloud computing in finance. Lenders should also devise credit products and risk-assessment methods that suit SMEs, so that borrowing becomes cheaper and funding easier to obtain.

Second, SMEs should deploy the funds they raise through digital finance with an eye to both long-run investment and short-run financial resilience. R&D, innovation, and digitalization projects deserve careful appraisal. Near-term results should be monitored, and expansion that expected returns cannot justify should be avoided. Public agencies and financial institutions can help by offering financial-management and investment-advisory services alongside credit.

Third, access to digital financial services should continue to widen, especially for smaller firms, although the gap between size groups is not statistically significant in the estimates. Products ought to be designed around how small firms actually operate. Regulators, meanwhile, should reinforce privacy protection and data governance, tighten prudential supervision of digital finance platforms, and guard against algorithmic discrimination, so that innovation does not breed undue systemic risk.

References

[1] Sun, R., Shang, Q., Zu, A., & Gan, S. (2026). How does digital finance affect financing constraints of SMEs? Evidence from China. *Applied Economics, 58*(2), 363–381. https://doi.org/10.1080/00036846.2025.2453248

DOI: 10.54254/2754-1169/2026.39166

[2] Dai, D., Fu, M., Ye, L., & Shao, W. (2023). Can digital inclusive finance help small- and medium-sized enterprises deleverage in China? *Sustainability, 15*(8), Article 6625. https://doi.org/10.3390/su15086625
[3] Tang, Y., & Geng, B. (2024). Digital finance development level and corporate debt financing cost. *Finance Research Letters, 60*, Article 104825. https://doi.org/10.1016/j.frl.2023.104825
[4] Xie, J., Wang, S., Chen, L., & Liu, Y. (2025). Digital finance, managerial ability, and corporate financing costs. *Finance Research Letters, 78*, Article 107235. https://doi.org/10.1016/j.frl.2025.107235
[5] Zhu, D., Wang, J., & Wang, S. (2025). Digital finance, investor sentiment, and corporate investment and financing. *International Review of Financial Analysis, 108*, Article 104664. https://doi.org/10.1016/j.irfa.2025.104664
[6] Chang, K., Cheng, X., Wang, Y., Liu, Q., & Hu, J. (2023). The impacts of ESG performance and digital finance on corporate financing efficiency in China. *Applied Economics Letters, 30*(4), 516–523. https://doi.org/10.1080/13504851.2021.1996527
[7] Xu, Y., Wang, Y., Lu, F., & Sheng, D. (2024). A study of the impact of digital inclusive finance on firm value from the perspective of financing constraints. *Applied Economics, 56*(33), 4033–4047.
[8] Li, S., & Xie, N. (2025). The impact of digital finance on firms' digital transformation: Mechanism analysis based on enterprise financing. *International Review of Economics & Finance, 101*, Article 104223. https://doi.org/10.1016/j.iref.2025.104223
[9] Ning, C.-Y., & Shun, H. (2025). Can digital finance promote the digital technology innovation of enterprises? *Finance Research Letters, 86*, Article 108555. https://doi.org/10.1016/j.frl.2025.108555
[10] Fu, J., Wan, X., & Irfan-Ullah. (2026). Role of digital finance in driving corporate environmental performance. *Spanish Journal of Finance and Accounting, 55*(2), 255–289. https://doi.org/10.1080/02102412.2026.2612895
[11] Chu, C., & Lv, Y. (2025). Digital finance, financing dilemma and corporate tax avoidance: Empirical evidence from A-share listed companies in China. *SAGE Open, 15*(2), 1–16. https://doi.org/10.1177/21582440251338909
[12] Zhou, R., & Ji, M. (2026). Unlocking productivity: How digital finance catalyzes manufacturing's new-quality capabilities. *International Review of Economics & Finance, 107*, Article 105143. https://doi.org/10.1016/j.iref.2026.105143
[13] Fan, J., Wang, K., & Xu, M. (2025). Does digital finance development affect corporate cash holdings? Evidence from China. *Technology Analysis & Strategic Management, 37*(12), 2970–2983. https://doi.org/10.1080/09537325.2024.2389137
[14] Han, W., Zhang, T., Khan, J., Wang, L., & Tu, C. (2024). Going global in the digital era: How digital finance affects Chinese OFDI. *Journal of Organizational and End User Computing, 36*(1), 1–22. https://doi.org/10.4018/JOEUC.334707