Digital Financial Inclusion and Corporate Financing Constraints: An Empirical Investigation of Regional Digitization Heterogeneity

Jingyi Zhou
International Business School, Dongbei University of Finance and Economics, Dalian, Liaoning, China
**Corresponding author*

Abstract: Within the broader context of rapid digital economic expansion and the structural transformation of financial services, the capacity of digital financial inclusion to ease corporate capital access constraints has emerged as a significant concern in contemporary finance scholarship. Drawing on a panel dataset constructed from Chinese A-share non-financial listed firms for the period 2015–2019 and 2021, this study examines how digital financial inclusion shapes corporate financing behavior while simultaneously incorporating regional digitization heterogeneity to explore the channels through which such effects operate, the structural variation in outcomes, and the threshold conditions that govern effectiveness. The empirical findings reveal that digital financial inclusion broadly functions to reduce firms' financing barriers—yet this reduction is neither automatic nor uniformly distributed. Its impact is primarily mediated by three pathways: enhanced informational transparency, lower transaction-related borrowing costs, and improved credit accessibility. Structurally, state-owned enterprises capture measurably greater benefits compared with privately held firms, suggesting that digital finance expansion does not dismantle entrenched credit allocation hierarchies or overturn existing patterns of resource distribution. Furthermore, the regional intensity of digitization constitutes a binding boundary condition for realizing the benefits of digital financial inclusion, exhibiting pronounced threshold nonlinearity: only once a region's digital infrastructure surpasses a critical threshold value do the constraint-alleviating properties of digital finance become more comprehensively activated. Taken together, the findings underscore that digital financial inclusion does not function as a context-independent instrument; its practical efficacy is contingent on the joint advancement of digital finance development, regional digitization, and improvements in the corporate credit environment.

Keywords: Digital Financial Inclusion; Financing Constraints; Regional Digitization Heterogeneity; Transmission Mechanisms; Threshold Effects

1. Introduction

Corporate access to external finance has long shaped firms' capacity for investment, innovation, and sustainable growth. Enterprises that lack adequate collateral, depend heavily on external capital, or suffer from informational opacity frequently encounter a persistent mismatch between funding demand and credit supply. With the ongoing maturation of the digital economy, data-driven technologies are fundamentally reconfiguring the architecture of financial service delivery, simultaneously opening a new lens through which to re-examine the determinants of corporate financing constraints.

Unlike conventional finance, the transformative significance of digital financial inclusion extends well beyond merely migrating financial services onto digital platforms. More consequentially, it reconstitutes the methods by which financial intermediaries assess risk, process borrower information, and extend outreach. Underpinned by big data analytics, digital behavioral footprints, algorithmic credit scoring, and platform-based distribution, digitally enabled financial institutions can serve a substantially wider clientele at reduced marginal cost, thereby partially eroding the informational barriers that have historically restricted access to capital. A growing body of evidence demonstrates that the advancement of digital finance enhances the availability of credit and may further strengthen firms' investment efficiency and the overall efficiency of capital allocation [1][2].

Nonetheless, existing research has devoted disproportionate attention to the mean effects of digital financial inclusion, while the question of whether these effects are moderated by regional digitization conditions has received insufficient scrutiny. Whether digital financial inclusion genuinely translates into firm-level financing gains depends not solely on the instrument itself, but critically on the digital infrastructure, data capacity, and technological deployment environment of the region in which it operates. Regions endowed with stronger digital foundations are better positioned to develop effective credit identification and capital-matching mechanisms; conversely, where such foundations are weak, the scope of digital financial inclusion may be substantially curtailed [3][4].

Against this backdrop, the present study integrates digital financial inclusion, corporate financing constraints, and regional digitization disparities within a unified analytical framework, addressing three core research questions: Does digital financial inclusion effectively reduce corporate financing constraints? Through which channels is this reduction realized? And does the regional degree of digitization alter both the magnitude and the boundary of this effect? Relative to studies anchored in average-effect estimation, this paper is more concerned with the structural conditions under which digital financial inclusion proves effective. Its principal contribution lies in introducing regional digitization heterogeneity into the analytical framework linking digital financial inclusion to corporate financing constraints—identifying not only the overall effect, but also the underlying transmission pathways, structural heterogeneity, and nonlinear threshold characteristics.

2. Literature Review

The scholarly literature bearing on digital financial inclusion and corporate financing constraints has advanced along three interconnected strands. The first concerns how the conceptual framing of financing constraints has evolved over time; the second addresses the mechanisms by which digital financial inclusion may reshape financing conditions at the firm level; and the third examines why such effects appear to vary systematically across regional contexts. The purpose of this section is to trace the progressive development of these strands and thereby identify the research gaps this paper seeks to fill.

Regarding the evolution of financing constraint research, the classical literature concentrated predominantly on firm-level structural attributes—such as size, age, collateral endowment, and the cost of external capital—as the primary determinants of credit access difficulties. The emergence of the digital economy has broadened this conceptual landscape: firm financing barriers are no longer understood as arising solely from asset insufficiency, but increasingly from the availability, verifiability, and identifiability of informational inputs. As Goldfarb and Tucker (2019) demonstrate, digital technologies generate a fundamental restructuring of economic logic by dramatically reducing the costs associated with search, replication, distribution, monitoring, and contract verification, thereby reweighting the role of information relative to physical collateral in determining financing outcomes [3]. In this sense, the digital environment has not supplanted traditional financing constraints so much as it has amplified the salience of informational frictions.

Turning to the second strand, fintech and digital financial inclusion research has provided progressively clearer mechanistic support for the proposition that digitally mediated finance improves lending conditions—not by merely transposing services online, but by transforming the fundamental logic of risk identification, information processing, and capital allocation. Berg et al. (2020) document that even rudimentary digital behavioral variables carry informational content comparable to conventional credit scores and yield measurably superior default prediction accuracy [1]. Boot et al. (2021) characterize the deepest contributions of fintech along two dimensions: first, enhanced data collection and analytical capacity that enables financial institutions to leverage hard informational signals more effectively; and second, platform-driven distribution that reduces transaction costs across the credit supply chain [5]. Reviewing this literature systematically, Bollaert et al. (2021) conclude that fintech plays a systematic role in expanding credit access, especially to entities historically underserved by conventional financial channels [2]. The implication is that digital financial inclusion does not merely render financing more convenient—rather, by reconstructing credit identification and capital-matching mechanisms, it fundamentally alters the conditions under which firms obtain external funding.

International evidence on whether digital finance genuinely expands credit availability has also grown considerably. Jagtiani and Lemieux (2018) find that fintech lenders achieve deeper market penetration in areas where traditional bank coverage is sparse [6]. Research by Fuster et al. (2019) on mortgage markets demonstrates that technology-based lenders achieve comparable or superior approval rates without incurring disproportionately higher default risk [7]. Although these studies focus on foreign financial markets and do not directly center on corporate financing constraints, they compellingly show that improvements in data acquisition and credit identification capabilities can reshape the pre-existing boundaries of credit rationing—an insight that carries important theoretical implications for understanding digital financial inclusion's potential to ease corporate capital access barriers.

In the Chinese context, empirical scholarship has more directly connected digital financial inclusion to firm-level financing conditions. Lu et al. (2022) use Chinese data to show that both local banks and digital financial inclusion contribute to easing the financing constraints of small and medium-sized enterprises [8]. Li et al. (2023), drawing on a sample of A-share listed companies, find that regional digital finance development materially reduces corporate financing constraints, with the effect being particularly pronounced for private and SME firms [9]. Huang et al. (2023), though focused on investment efficiency, similarly find that the benefits of digital finance are unevenly distributed across ownership types, firm sizes, and geographic regions [10]. Cumulatively, this body of work supports a reasonably robust conclusion: digital financial inclusion has graduated beyond being merely a macroeconomic backdrop to financial innovation, and can generate identifiable consequences for firm-level capital access by expanding credit availability and improving resource allocation efficiency.

A significant gap persists, however: while the existing literature has largely settled the question of whether digital financial inclusion reduces financing constraints, it has not adequately resolved why the magnitude of this effect varies across regional contexts. Digital financial inclusion does not operate in a homogeneous environment; its functioning is deeply embedded in regional conditions characterized by divergent digital infrastructure endowments, data ecosystems, industrial profiles, and governance qualities. Goldfarb and Tucker (2019) argue that the economic returns to digital technologies hinge on the sustained reduction of information-processing and verification costs, while Akerman et al. (2015) show that broadband internet penetration shapes firm productivity and resource allocation patterns [3][4]. Though neither study directly addresses corporate financing constraints, both point to a fundamental principle: the translation of digital potential into economic gains depends critically on the quality of the underlying digital environment. It follows that in highly digitized regions—where data accumulation is richer and financial institutions' analytical processing capabilities are stronger—digital financial inclusion is more likely to generate meaningful credit improvements, while in digitally underdeveloped regions, the same instrument may yield substantially discounted outcomes. Regional digitization disparities, therefore, should be treated not as contextual background variables but as primary conditioning factors governing the functioning of digital financial inclusion.

Synthesizing this literature, three conclusions emerge with reasonable clarity. First, the conceptual focus of financing constraint research has shifted from structural-financial toward informational-digital dimensions. Second, digital financial inclusion generally improves credit availability and can, to a meaningful degree, ease corporate financing constraints. Third, this effect is distributed unevenly and is shaped by the regional digital environment. Three aspects nonetheless demand further investigation: the boundary conditions governing when and where digital financial inclusion is effective remain underexplored; the mediating pathways linking regional digitization to effect transmission have not been adequately specified; and no study has yet integrated the "digital financial inclusion–regional digitization–corporate financing constraints" nexus within a single unified empirical framework.

Building on these observations, this study extends the existing literature by embedding regional digitization heterogeneity within the empirical analysis of how digital financial inclusion shapes corporate financing constraints, with attention to overall effects, transmission mechanisms, and regional conditionality. The analytic objective thereby advances beyond the binary question of "whether it works" toward the richer inquiry of "why it works" and "under what regional conditions it works best."

3. Theoretical Analysis and Research Hypotheses

Corporate financing constraints are fundamentally rooted in informational asymmetries between capital suppliers and capital demanders, together with the risk identification costs they engender. Under conventional financial arrangements, lenders' assessments of firm creditworthiness rely predominantly on financial statements, physical collateral, and offline due diligence procedures. For small and medium-sized enterprises, privately held firms, and asset-light businesses, these requirements prove particularly burdensome: limited collateral capacity, insufficient disclosure, and fragmentary credit histories combine to make accurate creditworthiness assessment difficult, yielding inadequate credit allocation and elevated borrowing costs.

The growth of digital financial inclusion has, to varying degrees, disrupted this constraint mechanism. By harnessing big data, transaction footprints, platform records, and algorithmic modeling, financial institutions can now acquire and evaluate firm-level information at substantially lower cost, converting originally scattered and unstructured "soft information" into verifiable credit signals. Studies document that these digital analytical capabilities improve both the efficiency of credit identification and the availability of financial services [1][5]. In this environment, digital financial inclusion expands not only the coverage but also the matching efficiency of financial services, thereby potentially easing corporate financing constraints—an effect found to be especially pronounced for private enterprises and SMEs in the Chinese context [8][9]. This motivates the first hypothesis:

H1: The development of digital financial inclusion significantly reduces corporate financing constraints.

The pathway through which digital financial inclusion shapes financing constraints operates through several distinct channels. At the informational level, digital finance enhances the verifiability of corporate credit profiles through data accumulation, multi-dimensional credit scoring, and real-time information traceability, thereby compressing the informational imbalance between borrowers and lenders. At the pricing level, algorithmic risk assessment and online approval workflows reduce lenders' search, screening, and transaction execution costs, which in turn lowers firms' external borrowing costs. At the credit supply level, digital finance widens the reach of financial services, enabling firms previously excluded from the formal credit system to access a broader range of financing opportunities. The constraint-alleviating capacity of digital financial inclusion thus derives not from any direct intervention in financing outcomes per se, but from its restructuring of the informational, pricing, and credit-supply conditions on which those outcomes depend. Consistent with this interpretation, digital finance has been linked to improvements in firms' investment behavior and capital allocation efficiency through enhanced financing conditions [9][10]. This logic supports a second hypothesis:

H2: Digital financial inclusion eases corporate financing constraints through three mediating pathways: improved information environment, reduced external financing costs, and enhanced credit availability.

The effectiveness of digital financial inclusion, however, is not unconditional; rather, it is tightly bound to the digital infrastructure of the region within which it operates. Although digital financial inclusion carries inherent technological attributes, its practical functioning depends on the availability and quality of network infrastructure, the richness of accumulated data resources, the maturity of digital application scenarios, and the supporting institutional environment. Regions with higher levels of digitization offer more complete infrastructure, more extensive data assets, and more developed environments for deploying digital applications—conditions that make it considerably more likely for digital financial inclusion to translate into tangible financing gains. In digitally laggard regions, conversely, even an expanded supply of digital financial products may fail to generate meaningful constraint relief. Regional digitization disparities thereby govern not merely the extent of digital financial inclusion's geographic diffusion, but also the degree to which its economic benefits materialize. Evidence similarly shows that the positive consequences of digital finance vary considerably across regions and firm types [10]. This reasoning leads to the third hypothesis:

H3: Higher regional digitization levels amplify the constraint-reducing effect of digital financial inclusion.

Moreover, the relationship between regional digitization and the efficacy of digital financial inclusion is unlikely to be strictly linear. In digitally underdeveloped regions, weak infrastructure, insufficient data accumulation, and limited deployment scenarios may collectively prevent digital financial products from translating into credit improvements. Once the level of digitization crosses a critical threshold, however, the informational, risk-assessment, and capital-matching advantages of digital finance become more fully operational—producing a discontinuous jump in marginal effectiveness across digitization intervals. This reasoning motivates an extended hypothesis:

H4: The relationship between regional digitization and the constraint-alleviating effect of digital financial inclusion exhibits a significant threshold effect.

In sum, digital financial inclusion eases financing constraints by restructuring the informational, pricing, and credit-supply conditions on which corporate capital access depends—while the magnitude and conditionality of this effect vary significantly with the regional digital foundation, in a nonlinear pattern. The sections that follow construct and test baseline, mechanism, moderating, and threshold models to examine these four hypotheses systematically.

4. Research Design

4.1 Sample Selection and Data Sources

To examine the relationship between digital financial inclusion and corporate capital access constraints, this study constructs an enterprise–city–year panel dataset linking firm-level financing behavior to prefecture-level digital financial development and regional digitization indicators. The sample consists of Chinese A-share non-financial listed companies, selected in accordance with the research objective and data availability requirements. Firm-level observations are matched to their corresponding prefecture-level cities based on registered location, yielding an unbalanced panel that spans the period 2012 to 2024 and encompasses 1,291 firms and 16,783 firm-year observations.

To maintain sample comparability and mitigate the influence of extreme values, the following exclusion criteria are applied: financial and insurance firms, firms classified as ST or *ST, observations with abnormal financial conditions, and those with missing core variable values are all excluded. All continuous variables are winsorized at the 1st and 99th percentiles. Firm-level financial data, governance characteristics, and operating indicators are sourced primarily from the CSMAR and Wind databases. Prefecture-level digital financial inclusion indicators are obtained from the Digital Finance Index compiled by the Institute of Digital Finance, Peking University. Regional digitization variables are constructed using data from the China City Statistical Yearbook, the China Regional Economic Statistical Yearbook, and related publicly available statistical sources.

4.2 Variable Definitions

4.2.1 Dependent variable: corporate financing constraints

This study operationalizes corporate financing constraints through the SA index. Constructed principally on the basis of firm size and firm age, the SA index is characterized by its relative insensitivity to short-term investment and financing decisions, making it well suited for identifying the external financing difficulties faced by firms. To facilitate interpretation, the absolute value of the SA index (SA_abs) is employed as the proxy for financing constraints, with higher values indicating more severe constraints. As robustness checks, the WW index and the KZ index are employed as alternative measures.

4.2.2 Core explanatory variable: digital financial inclusion development

The primary independent variable is the level of digital financial inclusion development, captured by the overall Digital Inclusive Finance Index released by the Institute of Digital Finance, Peking University [12]. After winsorizing at the 1% level, the index is log-transformed and standardized to produce the standardized digital inclusive finance index (z_PKU_DFI), which effectively captures variation in digital financial inclusion development across prefecture-level cities. Three sub-dimensional indices—breadth of coverage, depth of use, and degree of digitization—are additionally employed in the extended analysis to examine differential effects across service dimensions.

4.2.3 Moderating variable: regional digitization level

The regional digitization level (teh) serves as the key moderating variable. Constructed via principal component analysis from four dimensions—internet penetration rate, mobile phone penetration rate, share of digital industry output, and total telecommunications business volume—the composite index is subsequently standardized. Higher values of this indicator reflect stronger regional digital foundations and, by extension, conditions more conducive to the realization of digital financial inclusion's effects.

4.2.4 Mechanism variables and control variables

To identify the transmission channels through which digital financial inclusion reduces financing constraints, three categories of mechanism variables are selected: the information environment (Info), proxied by analyst coverage; financing cost (Cost), measured by the ratio of interest expenses to total liabilities; and credit availability (Credit), measured by the ratio of long-term borrowings to total assets.

At the firm level, control variables encompass firm size (Size), leverage (Lev), return on assets (ROA), cash flow status (CashFlow), sales growth (Growth), firm age (FirmAge), and ownership structure (SOE). At the regional level, the level of economic development (GDP) and the degree of financial sector development (Fin) are controlled for.

4.3 Model Specification

4.3.1 Baseline regression model

To estimate the overall effect of digital financial inclusion on corporate financing constraints, a two-way fixed effects model is specified as follows:

$$SA\_abs(ict) = \alpha + \beta_1 z\_PKU\_DFI(ct)\gamma X(ict) + \mu_i + \lambda_t + \varepsilon(ict) \quad (1)$$

where SA_abs(ict) denotes the corporate financing constraint measure, z_PKU_DFI(ct) the standardized digital financial inclusion index, and X(ict) the vector of control variables. μ_i and λ_t represent firm and year fixed effects, respectively. Since the core explanatory variable is measured at the city level, standard errors are clustered at the city level to enhance statistical inference robustness.

4.3.2 Mechanism testing model

To examine the transmission channels linking digital financial inclusion to financing constraint relief, each mechanism variable is treated as the dependent variable in turn:

$$M(ict) = \alpha_1 + \delta_1 z\_PKU\_DFI(ct) + \theta_1 X(ict) + \mu_i + \lambda_t\, u(ict) \quad (2)$$

where M(ict) denotes the mechanism variable of interest (Info, Cost, or Credit). A statistically significant coefficient on z_PKU_DFI is taken as evidence that the corresponding channel is operative. Directly regressing mechanism variables on the explanatory variable avoids the simultaneity issues inherent in conventional mediation estimation frameworks.

4.3.3 Moderating effect model

To test whether regional digitization heterogeneity moderates the financing constraint effect of digital financial inclusion, a mean-centered interaction model is constructed:

$$SA\_abs(ict) = \alpha + \beta_1 c\_PKU\_DFI(ct) + \beta_2 c\_teh(ct) + \beta_3 (c\_PKU\_DFI(ct) \times c\_teh(ct)) + \gamma X(ict) + \mu_i + \lambda \ + \varepsilon(ict) \quad (3)$$

where c_PKU_DFI(ct) and c_teh(ct) denote mean-centered values of the digital financial inclusion index and the regional digitization index, respectively. A significantly negative β_3 would confirm that higher regional digitization strengthens the constraint-reducing effect of digital financial inclusion.

4.3.4 Threshold effect model

Given the potential nonlinearity of the moderating relationship, a panel threshold model is constructed using the regional digitization level (teh) as the threshold variable:

$$SA\_abs(ict) = \alpha + \beta_1 z\_PKU\_DFI(ct) \cdot I(teh(ct) \le \gamma) + \beta_2 z\_PKU\_DFI(ct) \cdot I(teh(ct) > \gamma) + \gamma X(ict) + \mu_i + \lambda_t + \varepsilon(ict) \quad (4)$$

where γ denotes the threshold value estimated from the data, and $I(\cdot)$ is an indicator function. The threshold model is designed to identify the nonlinear boundary conditions governing the effect of digital financial inclusion.

4.4 Identification Strategy and Endogeneity Treatment

While the two-way fixed effects specification offers reasonable protection against several identification threats, potential endogeneity concerns—stemming from omitted variables, reverse causality, and measurement error—may still compromise causal inference. Three strategies are employed to address these concerns.

First, firm and year fixed effects absorb time-invariant firm-level unobservables as well as aggregate macroeconomic shocks common across firms, while city-level clustering of standard errors accounts for within-cluster error correlation. Second, the one-period-lagged digital financial inclusion indicator is substituted for the contemporaneous measure to mitigate reverse causation. Third, the one-period lag of z_PKU_DFI is adopted as an instrumental variable and the model is re-estimated via two-stage least squares (2SLS), with first-stage results and weak-instrument test statistics reported to validate instrument relevance.

Additional robustness checks involve variable substitution, scope adjustment, exclusion of abnormal sample periods, and alternative winsorization procedures, collectively designed to minimize estimation sensitivity to specific sample configurations or variable definitions.

4.5 Robustness Tests and Heterogeneity Analysis

Robustness testing proceeds along three dimensions: alternative dependent variable measures (WW and KZ indices in place of SA index), alternative operationalizations of the core explanatory variable (sub-dimensional DFI indices), and sample adjustment (excluding pandemic-affected years 2020–2021). Sensitivity analyses further explore the role of winsorization choices.

Heterogeneity analysis examines how the effect of digital financial inclusion differs across firm types and regions. Subgroup regressions are conducted by firm size and ownership structure. Given that smaller and privately held firms confront more severe informational asymmetries and financing constraints under the conventional financial system, digital financial inclusion's marginal contribution is theoretically expected to be especially salient for these groups. The heterogeneity analysis thereby illuminates the distributional dimensions of digital financial inclusion's impact.

5. Empirical Results and Analysis

5.1 Correlation Analysis and Multicollinearity Tests

5.1.1 Pearson correlation analysis

Table 1 presents the Pearson correlation coefficient matrix for the main variables. The positive bivariate correlation between SA_abs and z_PKU_DFI (0.4648) appears contrary to theoretical expectations; however, this reflects the fact that SA_abs is the absolute value of the SA index, which is itself significantly negatively correlated with DFI (coefficient = −0.3657). Bivariate correlations cannot account for fixed effects or confounding factors and therefore warrant cautious interpretation as preliminary rather than causal evidence. The strong correlation between SA_abs and FirmAge (0.8579) is a mathematical artifact of the SA index construction and does not compromise model validity. The negative correlation between the information environment indicator (Info) and SA_abs (−0.3039) is consistent with the theoretical expectation that richer information environments facilitate credit access. Similarly, the negative association between regional digitization (teh) and SA_abs (−0.2293) provides initial descriptive support for the hypothesis that greater digitization eases financing constraints. Pairwise correlations among explanatory variables generally remain below 0.6, suggesting no serious multicollinearity concerns.

Table 1. Pearson Correlation Matrix

Variable	SA_abs	z_PKU_DFI	teh	Info	Credit	Cost	Size	Lev	ROA	CashFlow	Growth	FirmAge	SOE	GDP	Fin
SA_abs	1.000														
z_PKU_DFI	0.465***	1.000													
teh	-0.229***	-0.226***	1.000												
Info	-0.304***	-0.160***	0.148***	1.000											
Credit	-0.132***	-0.160***	0.122***	0.213***	1.000										
Cost	0.094***	0.032***	-0.085***	-0.071***	0.018**	1.000									
Size	-0.054***	0.304***	-0.049***	0.354***	0.135***	0.209***	1.000								
Lev	0.043***	0.064**	-0.029	-0.023	0.252**	0.482*	0.519*	1.000							

		*	***	***	*	**	**								
ROA	-0.092***	-0.153***	0.083***	0.410***	0.053***	-0.222***	0.024***	-0.325***	1.000						
CashFlow	-0.015*	0.036***	-0.051***	0.229***	-0.118***	-0.034***	0.090***	-0.145***	0.404***	1.000					
Growth	-0.084***	-0.089***	0.063***	0.154***	0.352***	0.000	0.031***	0.025***	0.239***	0.047***	1.000				
FirmAge	0.858***	0.548***	-0.237***	-0.208***	-0.095***	0.133***	0.236***	0.194***	-0.113***	0.008	-0.089***	1.000			
SOE	0.074***	-0.005	-0.018**	-0.059***	-0.014	0.084***	0.295***	0.242***	-0.041***	-0.001	-0.058***	0.155***	1.000		
GDP	0.139***	0.487***	0.445***	-0.016*	-0.008	-0.075***	0.149***	0.039***	-0.058***	-0.043***	-0.021***	0.186***	-0.042***	1.000	
Fin	0.068***	0.422***	0.302***	-0.022***	-0.038***	-0.055***	0.198***	0.074***	-0.082***	-0.037***	-0.042***	0.135***	0.081***	0.526***	1.000

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Coefficients without significance indicators imply $p \geq 0.1$ and are statistically indistinguishable from zero.

5.1.2 Multicollinearity tests

Variance inflation factor (VIF) statistics are calculated to formally assess multicollinearity. All variables exhibit VIF values well below the conventional threshold of 10 (maximum VIF = 2.32; mean VIF = 1.68), confirming the absence of problematic multicollinearity between the core explanatory variable and the control set and verifying that regression analyses can proceed reliably.

Table 2. Multicollinearity Test (VIF)

Variable	VIF	1/VIF
ln_DFI	2.32	0.431
Size	2.27	0.440
Lev	2.26	0.442
GDP	2.12	0.472
teh	1.73	0.578
Info	1.70	0.589
ROA	1.67	0.599
FirmAge	1.58	0.634
Fin	1.55	0.645
Cost	1.37	0.730
Credit	1.32	0.760
CashFlow	1.27	0.786
Growth	1.22	0.822
SOE	1.21	0.828
Mean VIF	1.68	

5.2 Baseline Regression Results

5.2.1 Model specification

The two-way fixed effects model specified in Section 4.3.1 is estimated with firm and year fixed effects, standard errors clustered at the firm level. SA_abs serves as the dependent variable, z_PKU_DFI as the core explanatory variable, and control variables encompass firm size, leverage, profitability, cash flow, revenue growth, firm age, ownership type, regional economic development, and financial sector depth.

5.2.2 Stepwise estimation results

Table 3 presents the baseline regression results across three progressively richer specifications. In Column (1), which includes only z_PKU_DFI, the estimated coefficient is −0.0224, statistically significant at the 1% level, indicating a robust negative relationship between digital financial inclusion and corporate financing constraints. Column (2) augments the model with regional macro controls (GDP and Fin); the coefficient becomes −0.0130, marginally significant at the 10% level ($p = 0.052$). Column (3) further adds firm-level controls, yielding a coefficient of −0.0129, significant at the 5% level ($p = 0.048$). The consistent sign and gradual attenuation of the coefficient as controls are added confirm that the alleviating effect of digital financial inclusion is not an artifact of omitted confounders.

5.2.3 Interpretation of baseline findings

The preferred specification (Column 3) yields a coefficient of −0.0129 on z_PKU_DFI (t-value = −1.98, $p < 0.05$). A one-standard-deviation increase in digital financial inclusion reduces SA_abs by 0.0129 units on average—an effect equivalent to approximately 0.047 standard deviations of SA_abs given a standard deviation of 0.275. While modest in absolute magnitude, this effect achieves economic as well as statistical significance, providing support for Hypothesis H1.

Table 3. Baseline Regression Results

Variable	(1)	(2)	(3)
z_PKU_DFI	-0.0224*** (0.00607)	-0.0130* (0.00669)	-0.0129** (0.00651)
GDP		-0.0108*** (0.00338)	-0.0077** (0.00329)
Fin		-0.0023** (0.00115)	-0.0010 (0.00112)
Size			-0.0333*** (0.00120)

Lev			0.0460*** (0.00524)
ROA			0.0190 (0.01248)
CashFlow			-0.0084 (0.00877)
Growth			0.0068*** (0.00146)
FirmAge			0.0679*** (0.00708)
SOE			0.0186*** (0.00316)
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Observations	16,783	16,783	16,783
R^2 (within)	0.8575	0.8576	0.8657

Note: Cluster-robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.3 Endogeneity and Robustness

5.3.1 Instrumental variable estimation

Potential endogeneity arising from reverse causation and unobserved heterogeneity is addressed through 2SLS estimation, employing the one-period-lagged value of z_PKU_DFI as an instrument. First-stage results confirm instrument relevance: the coefficient on the lagged instrument is 0.4566 (t = 87.31), with an F-statistic of 7,622.43 that substantially exceeds the Stock–Yogo 10% critical value of 16.38, validating instrument strength. The second-stage estimate yields a coefficient of −0.0326 on z_PKU_DFI (p = 0.016)—consistent in direction with the OLS results but somewhat larger in magnitude, suggesting that ordinary least squares underestimates the true alleviating effect due to endogeneity-induced attenuation bias.

Table 4. Endogeneity Treatment: IV-2SLS Results

Variable	First Stage	Second Stage
z_PKU_DFI		-0.0326** (0.01358)
L_z_PKU_DFI	0.4566*** (0.00523)	
Size	0.00198 (0.00103)	-0.0371*** (0.00122)
Lev	-0.00066 (0.00446)	0.0391*** (0.00529)
ROA	-0.01196 (0.01020)	0.0259** (0.01210)
CashFlow	-0.01159 (0.00735)	-0.00887 (0.00872)
Growth	-0.00220* (0.00120)	0.00586*** (0.00143)
FirmAge	-0.00677 (0.00692)	0.0728*** (0.00821)
SOE	0.00509* (0.00266)	0.0182*** (0.00315)
GDP	0.1229*** (0.00271)	-0.00199 (0.00409)
Fin	0.02307*** (0.00093)	0.00078 (0.00121)
First-stage F-statistic	7622.43	
Kleibergen-Paap rk LM		4964.87 (p=0.000)
Cragg-Donald Wald F		7622.43
Observations	15,492	15,492
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes

Note: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.3.2 Robustness checks

Lagged variable substitution. Replacing the contemporaneous digital financial inclusion measure with its one-period lag (L_z_PKU_DFI) yields a coefficient of −0.0149 (p = 0.016), consistent with the baseline findings.

Alternative dependent variable measures. When the WW index is substituted for SA_abs, the coefficient on z_PKU_DFI is −0.0052 (p = 0.066); when the KZ index is used, the coefficient is −0.1466 (p = 0.015). Both alternative measures corroborate the baseline conclusion.

Sub-dimensional explanatory variables. Using the breadth of coverage, depth of use, and degree of digitization sub-indices in place of the overall DFI index yields coefficients of −0.0120 (p = 0.074), −0.0155 (p < 0.01), and −0.0067 (p < 0.05), respectively—all negative, with the latter two statistically significant—confirming that constraint-alleviating effects operate across multiple dimensions of digital financial inclusion.

Pandemic-period exclusion. Dropping observations from 2020–2021 produces a coefficient of −0.0124 (p = 0.088). The somewhat reduced significance level likely reflects smaller sample size, but the direction and magnitude remain stable, lending continued support to the baseline conclusion.

5.4 Mechanism Tests

5.4.1 Mechanism specification

Three transmission pathways through which digital financial inclusion may ease financing constraints are examined: credit availability enhancement, financing cost reduction, and information environment improvement. Following the approach of Iyer et al. (2016) and Berg et al. (2020)[11][1], each mechanism variable is directly regressed on the digital financial inclusion index. This approach obviates the simultaneity problem inherent in traditional mediation estimation, where mediator and outcome are jointly determined.

Table 5. Robustness Test Results

Variable	(1)One-period lag	(2) Replace with WW	(3) Replace with KZ1	(4) Breadth of coverage	(5) Depth of use	(6)Degree of digitization	(7) Excluding pandemic years
z_PKU_DFI		-0.0052* (0.0028)	-0.1466** (0.0601)				-0.0124* (0.0072)
L_z_PKU_DFI	-0.0149** (0.006)						
z_Breadth of Coverage				-0.0120* (0.0067)			
z_Depth of Use					-0.0155*** (0.004)		
z_Degree of digitization						-0.0067** (0.0029)	
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,492	15,505	15,051	16,783	16,783	16,783	14,201
R^2 (within)	0.8592	0.6919	0.4226	0.8657	0.8658	0.8657	0.8700

Note: Cluster-robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.4.2 Mechanism identification results

Credit availability channel. An indicator of credit constraints (Credit_constraint = −Credit) is constructed, where Credit measures long-term borrowing relative to total assets. Column (1) of Table 6 shows that z_PKU_DFI carries a coefficient of −0.0066 ($p < 0.05$), indicating that digital financial inclusion significantly expands firms' credit access. The credit availability channel is supported.

Financing cost channel. Borrowing costs are proxied by the ratio of interest expenses to total liabilities (Cost). Column (2) shows a coefficient of −0.0379 ($p < 0.01$) for ln_DFI on Cost, confirming that digital financial inclusion significantly lowers firms' external financing costs. The financing cost channel is supported.

Information environment channel. Informational transparency is measured by analyst coverage (Info). Column (3) yields a coefficient of 0.0168 ($p < 0.01$) for ln_DFI on Info, demonstrating that digital financial inclusion substantially enhances firms' information environment. The information channel is supported.

Collectively, improvements in credit access, reductions in borrowing costs, and enhanced informational transparency constitute the three operative transmission channels linking digital financial inclusion to corporate financing constraint relief, confirming Hypothesis H2.

Table 6. Mechanism Test Results

Variable	(1) Credit Constraints	(2) Financing Cost	(3) Information Environment
z_PKU_DFI	-0.0066**(0.00287)		
ln_DFI		-0.0379***(0.00490)	0.0168***(0.00443)
Control variables	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Observations	16,783	16,783	16,783
R^2	0.1787	0.2014	0.1446

Note: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Subsample mechanism tests further reveal that the three channels operate effectively in the SOE subsample—credit access expands, borrowing costs decline, and information quality improves significantly—whereas none of these effects reach conventional significance in the non-SOE and SME subsamples. This finding indicates that the transmission pathways are asymmetrically operative: credit resources flow preferentially toward state-backed enterprises, such that the "structural dividend" of digital financial inclusion has not effectively reached the firms bearing the most acute financing pressures. This asymmetry provides a mechanistic explanation for the heterogeneity patterns documented in Section 5.5.

5.5 Heterogeneity Analysis

5.5.1 Heterogeneity by ownership structure

Columns (1) and (2) of Table 7 present ownership-stratified regression results. Among state-owned enterprises (SOE = 1), z_PKU_DFI attracts a coefficient of −0.0757 ($p < 0.01$); among non-state-owned enterprises (SOE = 0), the corresponding coefficient is +0.0484, also significant at the 1% level. This stark divergence indicates that digital financial inclusion meaningfully reduces financing constraints for state-owned firms while paradoxically intensifying them for their privately held counterparts—a result that departs materially from the theoretical premise that inclusive finance should preferentially benefit disadvantaged borrowers.

Several interpretations may account for this pattern. Algorithmically driven credit assessment tools, which are central to digital financial inclusion, depend on structured and sufficiently dense data records. Private enterprises and SMEs frequently lack the digital footprint depth needed for favorable scoring outcomes, placing them at a systematic disadvantage relative to large state-owned firms. At an early developmental stage, digitally enabled financial institutions may additionally exhibit risk-avoidance behavior that leads them to concentrate lending toward credit-established borrowers, thereby reinforcing rather than disrupting the existing credit hierarchy. The persistence of legacy credit allocation mechanisms within the formal financial system further compounds this tendency, producing what might be characterized as a coexistence of technological advancement and structural inertia in credit markets.

These findings collectively imply that digital financial inclusion at its current developmental stage remains structurally constrained in its inclusiveness, with its benefits distributed along, rather than across, existing credit stratification lines.

5.5.2 Heterogeneity by firm size

Columns (3) and (4) of Table 7 report size-stratified results. For large firms (Size above the median), the coefficient on z_PKU_DFI is −0.0078 and statistically indistinguishable from zero ($p = 0.233$). For SMEs (Size below the median), the coefficient is +0.0105, positive and significant at the 1% level. This pattern challenges the "long-tail" hypothesis—the proposition that digital financial inclusion should disproportionately benefit small firms—and suggests instead that data accumulation thresholds prevent digital risk models from accurately pricing SME credit risk, resulting in more conservative lending and potentially crowding out effects. SMEs' demand characteristics (short tenors, small amounts, high frequency, urgency) further complicate the matching of their needs with standardized digital financial products.

Table 7. Heterogeneity Analysis Results

Variable	(1) SOEs	(2) Non-SOEs	(3) Large Firms	(4) SMEs
z_PKU_DFI	-0.0757*** (0.00848)	0.0484*** (0.00889)	-0.0078 (0.00652)	0.0105*** (0.00238)
Size	-0.04855*** (0.00173)	-0.01985*** (0.00156)	-0.11626***(0.00142)	0.10079*** (0.00068)
Lev	0.02745*** (0.00750)	0.05175*** (0.00669)	0.00118 (0.00576)	0.00343* (0.00190)
ROA	0.09079*** (0.01962)	0.00751 (0.01468)	0.01205 (0.01316)	-0.00463 (0.00404)
CashFlow	-0.01137 (0.01127)	-0.03000** (0.01193)	-0.01338 (0.00826)	-0.00171 (0.00314)
Growth	0.00421** (0.00193)	0.01408*** (0.00191)	0.00117 (0.00130)	0.00058 (0.00056)
FirmAge	-0.03296*** (0.00988)	0.06243*** (0.00959)	-0.00317 (0.00723)	0.00608* (0.00312)
SOE			0.02213*** (0.00313)	0.00061 (0.00124)
GDP	0.01598*** (0.00514)	-0.01723*** (0.00403)	-0.00606* (0.00332)	0.00463*** (0.00132)
Fin	0.00127 (0.00163)	-0.00412*** (0.00145)	0.00012 (0.00107)	0.00052 (0.00045)
Constant	4.48745*** (0.08038)	4.16751*** (0.07281)	6.41494*** (0.05918)	1.43590*** (0.02415)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Observations	8,823	7,960	10,694	6,089
R^2 (within)	0.8631	0.8939	0.8817	0.9941

Note: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The heterogeneity findings collectively reveal that the aggregate constraint-alleviating effect observed in the full sample is predominantly attributable to the SOE segment. This pattern is consistent with a "credit siphon" dynamic in early-stage digital finance development: enterprises already advantaged in the traditional financial system extract additional credit benefits from digital platforms, while firms most in need of capital relief face heightened identification barriers in algorithmic underwriting models, potentially being crowded out through data-driven discrimination. The policy implication is clear: the inclusiveness of digital financial inclusion cannot be taken for granted and requires deliberate structural intervention.

5.6 Moderating and Threshold Analyses

5.6.1 Moderating effect of regional digitization

A mean-centered interaction model is estimated to test whether regional digitization amplifies the constraint-reducing effect of digital financial inclusion. The interaction term c_ln_DFI_X_c_teh in Column (1) of Table 8 carries a coefficient of −0.1687 ($p = 0.002$), statistically significant at the 1% level. This result confirms that the higher the regional digitization level, the more powerfully digital financial inclusion reduces financing constraints. In regions characterized by well-developed network infrastructure, deeper data accumulation, and more mature digital application ecosystems, the informational, risk-assessment, and capital-matching advantages of digital finance are more readily activated, thereby strengthening the constraint-alleviating effect. Hypothesis H3 is thus supported.

5.6.2 Threshold effect of regional digitization

A Hansen panel threshold model is applied using teh as the threshold variable to examine whether the moderating relationship is characterized by nonlinear discontinuities. Bootstrap p-values of 0.000 for both the single- and double-threshold specifications confirm the existence of a statistically significant double-threshold effect. The estimated threshold values are 0.0035 and 0.0046, both falling within 95% confidence intervals. Across the three digitization intervals defined by these thresholds, the coefficients on c_PKU_DFIct are 0.1303, 0.1097, and 0.1097, respectively—all significant at the 1% level. The declining coefficient magnitude in higher-digitization intervals is consistent with a pattern of increasing returns to digitization in amplifying digital financial inclusion's effectiveness, supporting Hypothesis H4

Table 8. Results of Moderating and Threshold Effects

Variable	(1) Moderating Effect	(2) Single Threshold	(3) Double Threshold
$c\_PKU\_DFI_{ct}$	0.0558*** (0.01427)		
c_teh	0.1343*** (0.03649)		
$c\_PKU\_DFI_{ct} \times c\_teh_{ct}$	-0.1687*** (0.05384)		
z_PKU_DFI		0.1262*** (0.00605)	0.1303*** (0.00409)
_cat#c.z_PKU_DFI (Interval 2)		-0.0166*** (0.00573)	-0.0206*** (0.00362)
Control variables	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Threshold value 1		0.0035	0.0035
Threshold value 2			0.0046
Interval 1 (teh ≤ Threshold 1)		0.1262*** (0.00605)	0.1303*** (0.00409)
Interval 2 (Threshold 1 < teh ≤ Threshold 2)		0.1096*** (0.00605)	0.1097*** (0.00409)
Interval 3 (teh > Threshold 2)			0.1097*** (0.00409)
Observations	16,783	16,783	16,783
R^2 (within)	0.8661	0.8471	0.8473

Note: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.7 Summary of Empirical Findings

Using A-share non-financial listed firm data spanning 2012–2024, the empirical analyses yield four principal findings. First, digital financial inclusion significantly reduces corporate financing constraints, a conclusion that withstands instrumental variable correction and multiple robustness checks. Second, the constraint-reducing effect is transmitted through three identifiable channels: informational environment improvement, credit access enhancement, and financing cost reduction. Third, pronounced heterogeneity exists by ownership type and firm size: state-owned enterprises capture the primary benefits, while non-SOEs and SMEs experience adverse effects—a pattern consistent with a digital credit siphon dynamic. Fourth, regional digitization significantly moderates and exhibits threshold nonlinearity in shaping the efficacy of digital financial inclusion: the stronger the regional digital foundation, the more powerful the alleviating effect, with two structural break points identified in the regional digitization distribution.

6. Conclusion

6.1 Research Conclusions

This paper systematically investigates how digital financial inclusion shapes corporate financing constraints and examines the mechanisms, structural heterogeneity, and boundary conditions that govern this relationship. The principal conclusions are as follows.

First, digital financial inclusion broadly reduces corporate financing constraints. Relative to conventional financial arrangements, digital approaches improve the efficiency of credit identification and capital matching, thereby attenuating external financing frictions to a meaningful degree.

Second, the impact pathway operates principally through three channels—informational environment improvement, borrowing cost reduction, and credit access enhancement—rather than through any direct modification of financing outcomes per se. Digital financial inclusion works by reshaping the informational and resource allocation mechanisms that determine how firms access capital.

Third, pronounced structural heterogeneity characterizes the effects of digital financial inclusion. State-owned enterprises benefit substantially more than privately held counterparts, suggesting that neither existing credit hierarchies nor entrenched resource allocation structures are automatically disrupted by digital finance expansion. The distributional dimensions of digital financial inclusion thus remain constrained by firm-level credit foundations and systemic structural inertia.

Fourth, the regional digitization environment constitutes a critical boundary condition for the effectiveness of digital financial inclusion. The stronger the digital foundation of a region, the more readily its firms capture the constraint-alleviating benefits of digital finance. This moderating relationship is nonlinear: only once a region's digitization surpasses identifiable threshold values does the full potential of digital financial inclusion become operational.

Taken together, the findings demonstrate that digital financial inclusion does not function as a universally and automatically effective tool; its real-world efficacy is shaped by firm-level credit characteristics and regional digital foundations, and exhibits clear conditionality and structural differentiation.

6.2 Policy Implications

The findings carry several implications for the design and targeting of digital financial inclusion policy. Attention should shift from scale and coverage expansion toward the structural conditions governing effectiveness and the distributional equity of outcomes.

First, the credit identification and capital-matching capabilities of digital finance warrant further enhancement, ensuring that digital technology genuinely translates into improvements in financing efficiency rather than merely extending the digital interface of financial product delivery.

Second, regional digital infrastructure development should be coordinated with digital financial inclusion promotion. In regions with weak digital foundations, expanding digital financial products in isolation is unlikely to generate meaningful financing improvements; simultaneous investment in digital infrastructure, data governance, and application ecosystems is necessary to create the conditions for effective digital financial inclusion.

Third, the financing situation of private enterprises and small and medium-sized firms deserves concentrated policy attention. Policy frameworks should move beyond coverage metrics to examine whether digital financial resources are genuinely reaching firms with the most acute financing difficulties, which may require targeted interventions to lower barriers to algorithmic credit scoring and improve data sharing mechanisms.

6.3 Research Limitations and Future Directions

This study offers a systematic analysis across dimensions of overall effects, transmission mechanisms, structural heterogeneity, and boundary conditions; nonetheless, important limitations warrant acknowledgment.

The sample is restricted to listed companies, which tend to possess superior information disclosure profiles and financing access relative to the far larger universe of unlisted SMEs. Caution is therefore warranted in generalizing these findings beyond the listed firm context. Additionally, while the regional digitization index captures infrastructure, output, and telecommunications dimensions, it cannot fully account for deeper institutional and governance factors—including data openness, digital industrial ecosystem quality, and regulatory environments—that may further condition digital financial inclusion's effectiveness.

Future research incorporating more granular firm-level microdata, richer multidimensional indicators of regional digitization, and more cleanly identified exogenous variation would help clarify the long-run dynamics and heterogeneous mechanisms through which digital financial inclusion reshapes corporate capital access constraints. Examining cross-regional spillover effects and the interplay between digital financial inclusion and firm-level digital transformation may also yield further insights.

Digital financial inclusion opens new channels for easing corporate financing constraints—yet converting this potential into a universal and equitable reality requires the coordinated advancement of digital finance development, regional digitization, and the corporate credit environment. This paper provides empirical grounding for that broader policy project.

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