Fintech Adoption and the Financing Efficiency of Small and Medium Sized Enterprises: A Digital Inclusive Finance Perspective

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Abstract

This paper examines how fintech adoption at the firm level affects the financing efficiency of small and medium-sized enterprises in China, and identifies financing constraints as the transmission channel and the regional level of digital inclusive finance as the moderating condition. Using a panel of 15,432 firm-year observations drawn from enterprises listed on the SME board and the ChiNext board of the Shenzhen Stock Exchange between 2013 and 2023, financing efficiency is measured through a slacks-based super efficiency frontier model and fintech adoption is captured from the disclosure text of annual reports. Baseline regressions with year and industry fixed effects show that fintech adoption exerts a significant positive effect on financing efficiency, with a one standard deviation increase in adoption raising efficiency by approximately 4.9 percent of the sample mean. Mediation analysis establishes that financing constraints partially transmit this effect, accounting for roughly 30.6 percent of the total, while the remaining share is generated directly through better alignment between the timing of fund raising and the timing of expenditure. Moderation analysis shows that the regional digital inclusive finance index significantly amplifies the return to adoption, indicating that firm-level digital capability and local financial infrastructure are complementary rather than substitutable. Heterogeneity tests reveal that the efficiency gain is concentrated among non-state-controlled enterprises, whose access to bank credit is not supported by implicit guarantees, and is larger in central and western provinces than in the eastern coastal provinces, suggesting that digital adoption partially substitutes for a thin traditional financial infrastructure. Robustness checks using an alternative radial efficiency measure and a one-period lag of the core explanatory variable confirm the stability of the core findings.

Keywords

Fintech adoption, SME financing efficiency, financing constraints, digital inclusive finance, mediation analysis, moderation analysis, China.

1. Introduction

We aim to examine systematically how fintech adoption at the firm level affects the financing efficiency of small and medium sized enterprises in China, and to identify both the internal channel through which the effect is transmitted and the regional condition under which it is amplified.

We begin by testing the overall effect of fintech adoption on financing efficiency, clarifying whether the deployment of digital financial technologies inside an enterprise raises the ratio of financing output to financing input within the institutional environment of the Chinese capital

market. This provides direct empirical evidence for the core research question. The paper then introduces financing constraints as a mediating variable in order to establish whether the relief of capital scarcity is the pathway along which fintech adoption is converted into efficiency gains. The regional level of digital inclusive finance is further introduced as a moderating variable, making the interaction between the technological capability held by an enterprise and the digital financial infrastructure available in the city in which it operates observable. Given the diversity of ownership arrangements and the well documented gap between coastal and inland financial development in China, we additionally examine whether ownership nature and regional location generate significant differentiation in the intensity of the effect. By constructing and validating an analytical model that contains both a mediating variable and a moderating variable, we address a limitation of existing literature, in which fintech is generally treated as a macro level environment and its consequences are evaluated through the volume or the price of credit rather than through the efficiency with which raised capital is converted into operating results.

In China, small and medium sized enterprises supply the majority of urban employment, tax revenue and patent output, yet they remain the group most exposed to credit rationing. Conventional bank credit technology relies on collateral, audited statements and durable lending relationships, and the typical small enterprise can supply none of these at acceptable cost. The maturing of big data analytics, cloud computing, machine learning and distributed ledger systems has given rise to a set of financial technologies that alter the cost structure of screening and monitoring, and both financial institutions and borrowing enterprises can deploy these technologies.

Research conducted outside China has documented that technology based channels broaden the funding options available to smaller borrowers. Abbasi et al. [1] studied peer to peer lending platforms and found that this form of intermediation measurably improves the access of small and medium sized enterprises to external finance. Khan and Ahmad [2] examined fintech finance across a sample of developing and developed economies from 2013 to 2020 and found that fintech financing lowers the sensitivity of corporate investment to internal cash flow. This outcome is consistent with a genuine relaxation of credit constraints, and the effect is concentrated among small, young and privately held firms. Ha et al. [3] provided an overview of the state of the art on financial inclusion and fintech and concluded that the literature has converged on the view that digital technology reduces the unit cost of screening and monitoring borrowers who lack conventional credit histories.

Evidence from China points in the same direction. Chen et al. [4] used Chinese firm level data and demonstrated that fintech development significantly eases the financing constraints faced by small and medium sized enterprises. Yang et al. [5] measured financing constraints through the cash flow sensitivity of cash. The mitigating effect was found to be robust, and is stronger for privately owned firms, while both performance and risk rise as the level of fintech development increases. Li et al. [6] drew on companies listed on the National Equities Exchange and Quotations from 2011 to 2020 and found that fintech improves the performance of small and medium sized enterprises by enlarging financing scale and reducing financing cost. Li et al. [7] reported that fintech relieves financing constraints and thereby stimulates corporate green innovation. Fan et al. [8] examined manufacturing firms listed on the main boards between 2011 and 2020 and found that tighter financing constraints depress corporate liquidity, while fintech development moves liquidity in the opposite direction.

A parallel body of research centres on digital inclusive finance as a regional attribute. Bu et al. [9] established that digital inclusive finance significantly alleviates the financing constraints of small and medium sized enterprises. The depth of use matters more than the breadth of coverage, and the mechanism runs through reduced financing cost and controlled leverage. Digital inclusive finance was also found to correct the attribute mismatch, the field mismatch

and the regional mismatch embedded in traditional loan services. Zhang et al. [10] combined digitalization with financial inclusion and found that both dimensions improve the financing outcomes of Chinese small and medium sized enterprises. Li and Pang [11] found that digital inclusive finance compensates for the long tail effect in the financing process and raises the innovation capacity of smaller listed enterprises by correcting financial mismatch. Gu et al. [12] used enterprises listed on the SME board between 2011 and 2021 and verified the driving effect on innovation activities, noting that the effect varies with property rights and with technological attributes. Lee et al. [13] documented that digital inclusive finance supports the high quality development of Chinese enterprises, and Su et al. [14] reached a compatible conclusion when evaluating digital inclusive finance against the framework of the five development concepts.

Work on the supply side clarifies why these effects arise. Sheng [15] showed that fintech raises the credit that banks extend to small and medium sized enterprises. Feng et al. [16] matched loan level records of listed borrowers with the fintech patent holdings of their lending banks over the period from 2013 to 2022 and found that bank fintech lengthens feasible lending distance, with the reduction of information asymmetry and the improvement of risk management capacity identified as the operative channels. Yang et al. [17] used panel data covering 111 commercial banks from 2018 to 2021 and reported that the digital transformation of banks raises inclusive financial efficiency by altering the input of production factors.

A smaller set of studies addresses financing efficiency rather than financing volume. Guan et al. [18] examined 757 specialized, refined, niche and innovative small and medium sized enterprises listed in Shanghai and Shenzhen from 2013 to 2023 and found that supply chain finance raises financing efficiency while regional fintech development amplifies that positive effect. Xu et al. [19] evaluated the financing efficiency of high technology small and medium sized enterprises in the Yangtze River Delta and identified determinants located both inside and outside the enterprise. Liu and Fu [20] built a data envelopment model of financing efficiency for technology based small enterprises and treated financing constraints as the transmitting variable.

Two gaps remain in this literature. Most studies treat fintech as an environment surrounding the enterprise rather than as a capability that the enterprise itself acquires. Yet evidence at the household level reported by Yang and Zhang [21] indicates that adoption, and not mere availability, is what turns digital finance into realised inclusion. Furthermore, outcome measurement concentrates on how much capital is obtained and at what price, while the efficiency with which obtained capital is converted into operating output attracts far less attention. Xu et al. [22] suggest that inclusive digital finance changes the resilience of enterprises undergoing transformation rather than only the quantity of credit they receive.

We respond to both gaps. Fintech adoption is measured at the level of the individual enterprise from the disclosure text of annual reports, financing efficiency is measured on a slacks based super efficiency frontier that treats financing as a production process with identifiable inputs and outputs, and the regional digital inclusive finance index is used to estimate the infrastructure condition that governs how much a capability held inside the enterprise can actually deliver.

2. Conceptual Definition and Theoretical Foundation

2.1. Definition of Core Concepts

2.1.1. Fintech Adoption

Fintech adoption refers to the extent to which a non financial enterprise embeds digital financial technologies, including big data analytics, cloud computing, artificial intelligence, blockchain and digital payment infrastructure, into its own funding, settlement, credit and risk

management activities. The concept is distinct from the regional supply of fintech services. Two enterprises located in the same city may differ substantially in the intensity with which they use the services available to them. Following the firm level measurement logic used by Tang et al. [23], we estimate adoption through the frequency with which fintech related terms appear in the management discussion and analysis section of the annual report, on the reasoning that disclosure intensity reflects the strategic weight an enterprise attaches to the technology.

2.1.2. SME Financing Efficiency

Financing efficiency describes the relationship between the output an enterprise obtains from its financing activity and the resources the enterprise consumes in order to obtain that output. An enterprise that raises a large volume of funds at high cost, with long delay and with weak conversion into operating results is not efficient even though its financing scale is large. We therefore treat financing as a production process and evaluate it on an efficiency frontier, adopting the slacks based measure of super efficiency introduced by Tone [24]. The same modelling choice underlies the assessment of high technology small enterprises reported by Xu et al. [19].

2.1.3. Digital Inclusive Finance

Digital inclusive finance denotes the delivery of affordable and accessible financial services to underserved groups through digital channels. It is measured here with the Peking University Digital Financial Inclusion Index compiled by Guo et al. [25]. This index covers the breadth of coverage, the depth of usage and the degree of digitalization at the provincial, municipal and county levels, and it has become the standard regional indicator in this field.

2.2. Basic Theoretical Support

2.2.1. Credit Rationing Theory

Stiglitz and Weiss [26] demonstrated that when lenders cannot observe borrower quality, raising the interest rate worsens the pool of applicants through adverse selection and encourages riskier behaviour through moral hazard. Lenders therefore prefer to ration quantity rather than clear the market by price. Small and medium sized enterprises are precisely the borrowers whose quality is hardest to observe, which explains why they remain rationed even when they are willing to accept a higher price. Any technology that makes borrower quality observable at lower cost should consequently relax the rationing equilibrium and improve the terms on which capital is allocated.

2.2.2. Information Asymmetry and Pecking Order Theory

Myers and Majluf [27] demonstrated that when managers hold information that outside investors do not possess, external finance carries a lemons premium and enterprises follow an ordering that places internal funds ahead of debt and debt ahead of equity. The size of this premium is a direct function of the information gap. Fintech adoption narrows that gap by generating verifiable transaction records, by standardising the format in which operating data is transmitted and by allowing continuous rather than periodic monitoring. Both the premium and the efficiency loss attached to it should therefore fall.

2.2.3. Long Tail Theory

The long tail argument holds that a digital platform can serve a very large number of individually small customers profitably, because the marginal cost of service approaches zero once the platform has been built. Small and medium sized enterprises constitute the long tail of the credit market. The finding of Bu et al. [9] that usage depth matters more than coverage breadth is consistent with this logic, since depth reflects the intensity with which the tail actually transacts rather than the nominal reach of the network.

2.2.4. Transaction Cost Theory

Transaction cost reasoning treats the boundary and the form of an exchange as determined by the cost of searching, contracting and enforcing. Digital technologies compress each of these components. The evidence assembled by Feng et al. [16] that bank fintech extends feasible lending distance without raising the probability of default is an empirical expression of the same idea, because geographical distance serves as a proxy for the cost of acquiring and verifying soft information.

3. Research Hypotheses and Research Design

3.1. Research Hypotheses

3.1.1. The Impact of Fintech Adoption on SME Financing Efficiency

Fintech adoption acts on financing efficiency through the input side and the output side of the financing process at the same time. On the input side, digitalised settlement, invoicing and inventory records convert soft information into verifiable data. This shortens the due diligence cycle, lowers the intermediation margin demanded by lenders and reduces the volume of collateral required for a given loan. On the output side, real time visibility over cash position allows an enterprise to align the timing of fund raising with the timing of expenditure. Idle balances are thereby limited and the operating return generated per unit of capital raised is increased. Both mechanisms move the enterprise closer to the efficiency frontier without necessarily changing the scale of funds raised, and it is for this reason that efficiency rather than volume is the informative outcome. On this basis the following hypothesis is proposed.

H1: Fintech adoption significantly improves the financing efficiency of small and medium sized enterprises.

3.1.2. The Impact of Fintech Adoption on Financing Constraints

Financing constraints arise when the wedge between the cost of internal funds and the cost of external funds is large enough to force an enterprise to forgo positive value projects. The information gap between the enterprise and the capital supplier is the main source of this wedge. An enterprise that adopts digital financial technologies generates a continuous and machine readable record of its operations, allows lenders to verify that record at low cost, and gains access to funding channels such as supply chain platforms and digital credit products that do not depend on fixed asset collateral. The pool of accessible capital therefore widens and the price of external finance falls, which compresses the wedge. On this basis the following hypothesis is proposed.

H2: Fintech adoption significantly reduces the financing constraints faced by small and medium sized enterprises.

3.1.3. The Mediating Role of Financing Constraints

If fintech adoption compresses the wedge between internal and external funding costs, the resources released are not neutral with respect to efficiency. A less constrained enterprise can match the maturity of its liabilities to the life of its assets, can avoid the precautionary cash hoarding that depresses the return on capital and can decline expensive short term rollovers that inflate financing input without raising financing output. The relief of constraints therefore translates mechanically into a higher ratio of output to input on the financing frontier, which makes financing constraints a natural transmission variable between adoption and efficiency. On this basis the following hypothesis is proposed.

H3: Financing constraints play a mediating role in the process through which fintech adoption improves the financing efficiency of small and medium sized enterprises.

3.1.4. The Moderating Role of Digital Inclusive Finance

A capability held inside an enterprise delivers value only when there is a counterpart that can read the signal the capability generates. Digitalised operating records raise the efficiency of financing only if local financial institutions maintain the data interfaces, the risk models and the digital credit products needed to price those records. The regional level of digital inclusive finance therefore describes the absorptive capacity of the local financial system and should determine how much of a given level of adoption is converted into efficiency. Where the regional index is high, the marginal return to adoption should be larger. On this basis the following hypothesis is proposed.

H4: The regional level of digital inclusive finance positively moderates the effect of fintech adoption on the financing efficiency of small and medium sized enterprises.

Figure 1 presents the theoretical analysis framework that connects the four hypotheses, showing the direct path, the mediating path through financing constraints and the moderating path through the regional digital inclusive finance environment.

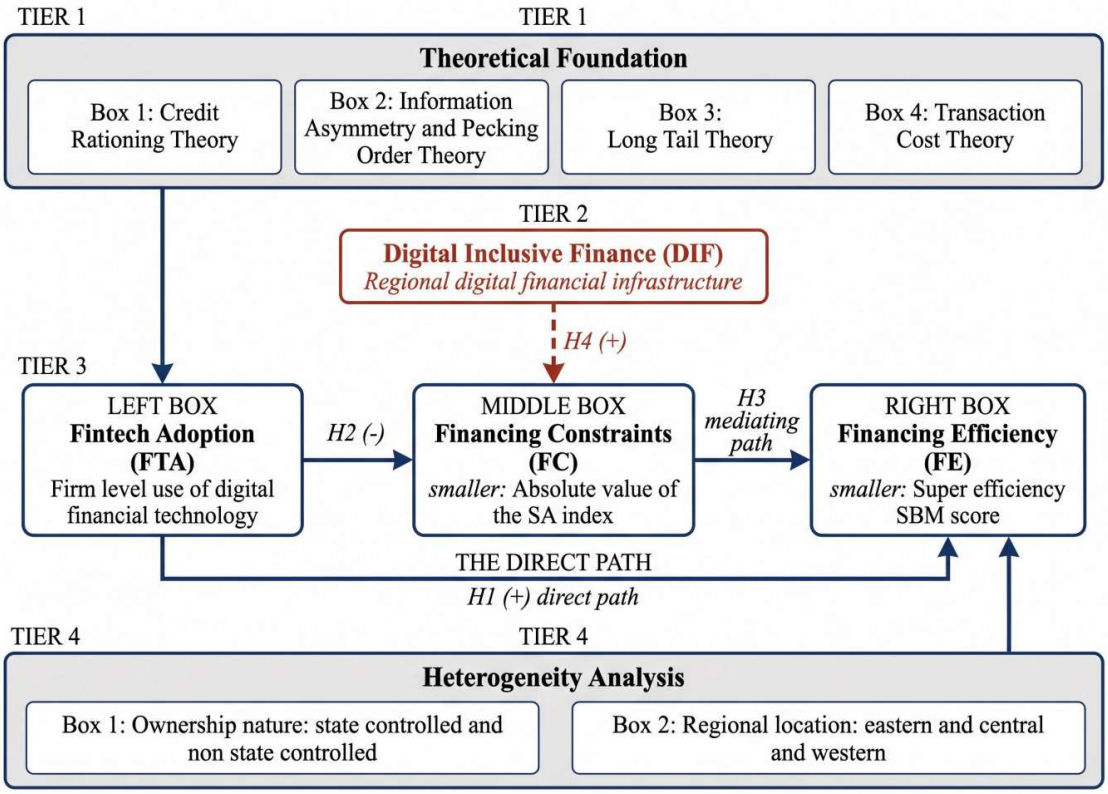


Figure 1. Theoretical Analysis Framework

3.2. Sample Selection and Data Sources

Enterprises listed on the SME board and the ChiNext board of the Shenzhen Stock Exchange from 2013 to 2023 are selected as the initial research sample for empirical testing. The selection steps are as follows. (1) Exclude enterprises in the financial and insurance industries, whose balance sheet structure is not comparable with that of industrial and service enterprises. (2) Exclude enterprises in delisting status or marked as ST. (3) Exclude observations with missing data for core variables during the sample period. (4) All continuous variables are winsorized at the 1st and 99th percentiles to limit the distorting influence of outlier observations on the regression estimates.

In total 15,432 firm year observations covering 1,876 listed enterprises were obtained. The annual report texts used to construct the adoption measure were downloaded from the official

disclosure platform of the Chinese securities market. The regional digital inclusive finance data come from the Peking University Digital Financial Inclusion Index [25] and are matched to the prefecture level city in which the registered office of each enterprise is located. All remaining financial indicators were retrieved from the CSMAR database.

3.3. Variable Design

The explained variable is financing efficiency, denoted by FE. Financing is treated as a production process in which an enterprise consumes financing resources and generates operating outcomes. The input indicators and the output indicators used in the efficiency measurement are reported in Table 1. The efficiency score is computed with the slacks based super efficiency model of Tone [24], which is non radial, incorporates input and output slacks directly into the objective function and permits scores above unity so that efficient units remain distinguishable from one another. The measurement model is given in equation (1).

$$\rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{\bar{s_i}}{x_{i0}}}{1 + \frac{1}{q}\sum_{r=1}^{q}\frac{s_r^+}{y_{r0}}} \tag{1}$$

In equation (1), ρ is the financing efficiency score of the evaluated decision making unit, m and q are the numbers of input and output indicators, x_{i0} and y_{r0} denote the level of input i and output r for the evaluated unit, and s_i^- and s_r^+ are the corresponding input excess and output shortfall. A larger value indicates that the enterprise converts financing resources into operating outcomes more effectively.

Table 1. Input and Output Indicators for the Measurement of Financing Efficiency

Category	Indicator	Measurement
Input	Financing scale	Sum of interest bearing debt and paid in capital divided by total assets
Input	Financing cost	Financial expenses divided by interest bearing debt
Input	Capital structure	Total liabilities divided by total assets
Output	Profitability	Return on total assets
Output	Growth	Growth rate of operating revenue
Output	Solvency	Current assets divided by current liabilities

The explanatory variable is fintech adoption, denoted by *FTA*. A dictionary of fintech related terms covering big data, cloud computing, artificial intelligence, blockchain, digital payment, digital credit and intelligent risk control is applied to the management discussion and analysis section of each annual report, and the total frequency of matched terms is recorded as $Freq_{i,t}$. Because the raw frequency is right skewed and takes the value zero for a non trivial share of observations, the measure is transformed as shown in equation (2).

$$FTA_{i,t} = ln(1 + Freq_{i,t}) \tag{2}$$

The mediating variable is financing constraints, denoted by *FC*. The SA index proposed by Hadlock and Pierce [28] is adopted because it is constructed only from firm size and firm age, both of which are exogenous to short run financing policy, so it avoids the endogeneity that affects indices built from financial ratios. The index is computed as shown in equation (3), and the absolute value is taken so that a larger value indicates a tighter constraint.

$$SA_{i,t} = -0.737Size_{i,t} + 0.043Size_{i,t}^{2} - 0.040Age_{i,t} \quad (3)$$

The moderating variable is digital inclusive finance, denoted by *DIF*. The city level aggregate index published by the Institute of Digital Finance of Peking University [25] is divided by one hundred so that its scale is comparable with the other regressors. Control variables cover firm size, leverage, profitability, growth, listing age, operating cash flow, ownership concentration and ownership nature, which is the control set commonly used in studies of digital finance and enterprise financing such as Li and Xie [29]. Definitions of all variables are reported in Table 2.

Table 2. Variable Definitions

Type	Symbol	Name	Measurement
Explained variable	FE	Financing efficiency	Super efficiency SBM score based on the indicators in Table 1
Explanatory variable	FTA	Fintech adoption	Natural logarithm of one added to the fintech term frequency
Mediating variable	FC	Financing constraints	Absolute value of the SA index
Moderating variable	DIF	Digital inclusive finance	City level digital financial inclusion index divided by one hundred
Control variable	Size	Firm size	Natural logarithm of total assets
Control variable	Lev	Leverage	Total liabilities divided by total assets
Control variable	ROA	Profitability	Net profit divided by total assets
Control variable	Growth	Growth	Growth rate of operating revenue
Control variable	Age	Listing age	Natural logarithm of one added to the number of listed years
Control variable	Cash	Operating cash flow	Net operating cash flow divided by total assets
Control variable	Top1	Ownership concentration	Shareholding percentage of the largest shareholder
Control variable	SOE	Ownership nature	Dummy variable equal to one for state controlled enterprises

3.4. Model Construction

To verify the effect of fintech adoption on financing efficiency, the transmitting role of financing constraints and the conditioning role of the regional digital environment, this paper constructs four regression models for empirical testing. All models are estimated with year fixed effects and industry fixed effects, and standard errors are clustered at the enterprise level.

Model (4) is used to examine the direct effect of fintech adoption on the financing efficiency of small and medium sized enterprises, and thereby to verify research hypothesis H1. The coefficient of interest is β_1.

$$FE_{i,t} = \beta_0 + \beta_1 FTA_{i,t} + \beta_2 Size_{i,t} + \beta_3 Lev_{i,t} + \beta_4 ROA_{i,t} + \beta_5 Growth_{i,t} + \beta_6 Age_{i,t} + \beta_7 Cash_{i,t} + \beta_8 Top1_{i,t} + \beta_9 SOE_{i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \quad (4)$$

Model (5) is used to analyse the relationship between fintech adoption and financing constraints, and to verify research hypothesis H2. A negative and significant α_1 would indicate that adoption loosens the constraint.

$$FC_{i,t}=\alpha_0+\alpha_1 FTA_{i,t}+\alpha_2 Size_{i,t}+\alpha_3 Lev_{i,t}+\alpha_4 ROA_{i,t}+\alpha_5 Growth_{i,t}+\alpha_6 Age_{i,t}+\alpha_7 Cash_{i,t}+\alpha_8 Top1_{i,t}+\alpha_9 SOE_{i,t}+\sum Year+\sum Industry+\mu_{i,t} \quad (5)$$

Model (6) is used to test the mediating effect of financing constraints in the process through which fintech adoption affects financing efficiency, and to verify research hypothesis H3. Partial mediation is indicated when γ_1 remains significant but falls below β_1 while γ_2 is significant.

$$FE_{i,t}=\gamma_0+\gamma_1 FTA_{i,t}+\gamma_2 FC_{i,t}+\gamma_3 Size_{i,t}+\gamma_4 Lev_{i,t}+\gamma_5 ROA_{i,t}+\gamma_6 Growth_{i,t}+\gamma_7 Age_{i,t}+\gamma_8 Cash_{i,t}+\gamma_9 Top1_{i,t}+\gamma_{10} SOE_{i,t}+\sum Year+\sum Industry+\nu_{i,t} \quad (6)$$

Model (7) introduces the regional digital inclusive finance index and its interaction with fintech adoption in order to verify research hypothesis H4. Both *FTA* and *DIF* are centred before the interaction term is formed, so that the coefficient δ_3 measures the change in the marginal effect of adoption when the regional index rises by one unit.

$$FE_{i,t}=\delta_0+\delta_1 FTA_{i,t}+\delta_2 DIF_{i,t}+\delta_3 FTA_{i,t}\times DIF_{i,t}+\delta_4 Size_{i,t}+\delta_5 Lev_{i,t}+\delta_6 ROA_{i,t}+\delta_7 Growth_{i,t}+\delta_8 Age_{i,t}+\delta_9 Cash_{i,t}+\delta_{10} Top1_{i,t}+\delta_{11} SOE_{i,t}+\sum Year+\sum Industry+\xi_{i,t} \quad (7)$$

4. Empirical Analysis

4.1. Descriptive Statistical Analysis

To describe the distributional characteristics of the sample and the dispersion of each variable, we perform descriptive statistical analysis on the 15,432 firm year observations. The corresponding results are presented in Table 3.

Table 3. Descriptive Statistics Results

Variable	Obs	Mean	Std. Dev.	Min	Max
fe	15432	0.612	0.238	0.104	1.243
fta	15432	1.427	1.086	0.000	4.263
fc	15432	3.716	0.281	3.012	4.517
dif	15432	2.684	0.673	0.912	4.315
size	15432	21.847	0.982	19.762	24.936
lev	15432	0.372	0.178	0.049	0.826
roa	15432	0.041	0.062	-0.196	0.212
growth	15432	0.163	0.348	-0.513	1.682
age	15432	2.784	0.371	1.609	3.434
cash	15432	0.048	0.071	-0.164	0.253
top1	15432	31.462	13.207	8.514	71.238
soe	15432	0.147	0.354	0.000	1.000

As Table 3 shows, the mean of financing efficiency is 0.612 with a standard deviation of 0.238, and values range from 0.104 to 1.243. A mean well below unity indicates that the typical sampled enterprise operates some distance inside the financing frontier, and a maximum above unity shows that the super efficiency specification separates the best performing units from one another. The core explanatory variable *FTA* has a mean of 1.427 with a minimum of zero, which shows that a portion of the sample discloses no fintech related content at all while the most intensive adopters cluster near the upper bound of 4.263. Financing constraints measured by the absolute SA index average 3.716 with limited dispersion, which is consistent with the construction of the index from slow moving firm attributes. The regional index of digital inclusive finance averages 2.684 and ranges from 0.912 to 4.315, confirming that the sampled enterprises operate in markedly different digital financial environments. State controlled enterprises account for 14.7 percent of the sample, reflecting the private dominance of the two boards under study.

Figure 2 traces the annual mean of fintech adoption alongside the annual mean of financing efficiency across the sample window. The two series move upward together after 2016, a period that coincides with the point at which digital credit products and supply chain financing platforms became widely available to smaller enterprises in China. This co movement gives preliminary visual support for the main hypothesis.

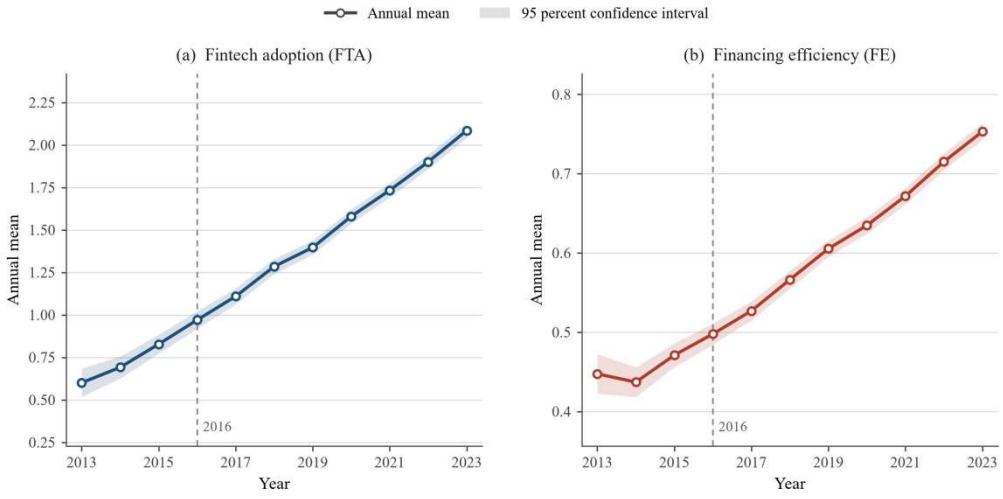


Figure 2. Annual Trends of Fintech Adoption and Financing Efficiency

4.2. Correlation Analysis

Figure 3 reports the pairwise correlation results for all variables entering the regression. The correlation coefficient between the explained variable *FE* and the core explanatory variable *FTA* is 0.277 and is significantly positive at the 1 percent level, which offers initial support for the expectation that fintech adoption raises financing efficiency. The correlation between *FTA* and the mediating variable *FC* is negative at -0.336 and significant at the 1 percent level, while the correlation between *FC* and *FE* is negative at -0.433, a pattern consistent with the proposed transmission path. The correlation between *FE* and the regional index *DIF* is 0.300 and significant at the 1 percent level. No pair of control variables exceeds an absolute correlation of 0.40, and collinearity is therefore unlikely to distort the estimates.

To check that the regressors are not seriously collinear, a variance inflation factor test was performed on each variable. As reported in Table 4, the mean variance inflation factor is 1.39 and every individual value lies well below the conventional threshold of ten, indicating that no pronounced multicollinearity is present among the variables entering the regression model.

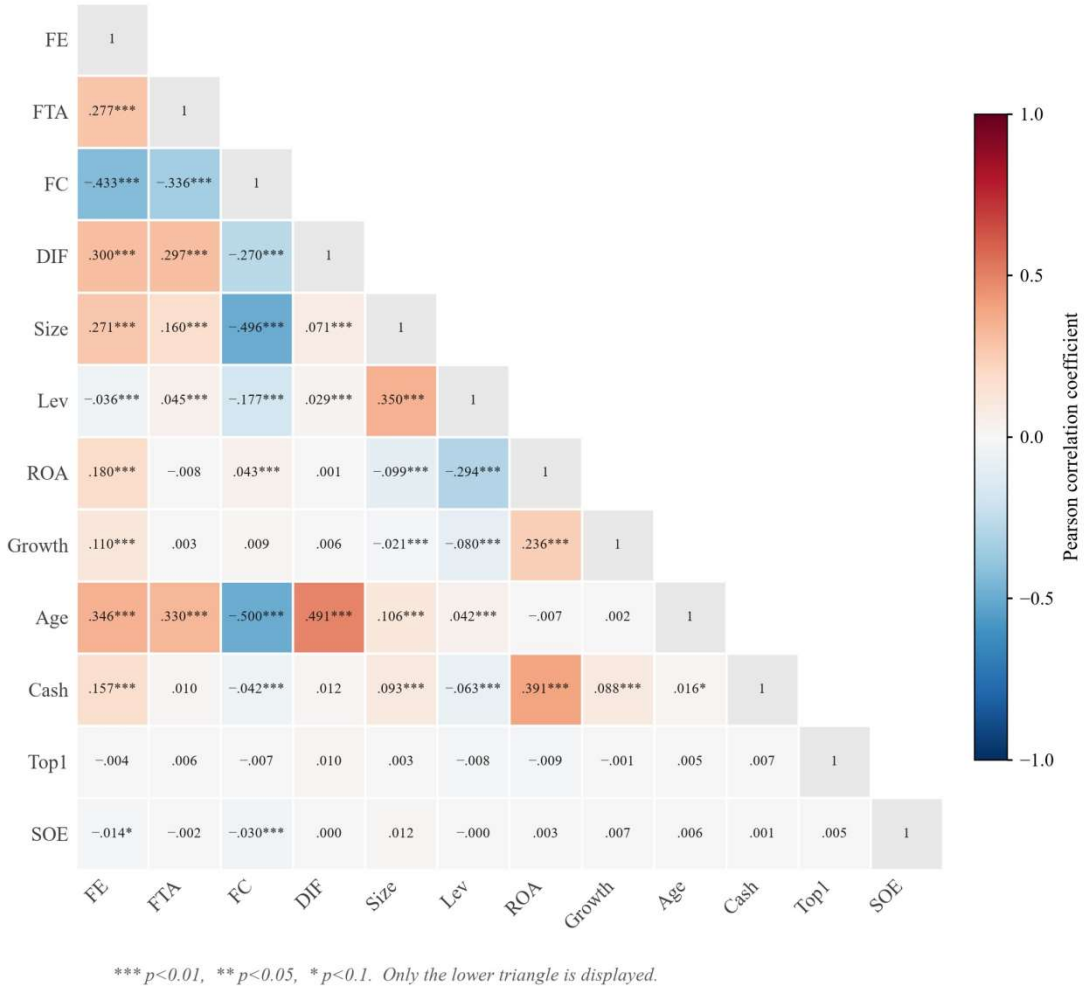


Figure 3. Pairwise Correlation Results

Table 4. Multicollinearity Analysis

Variable	VIF	1/VIF
size	1.94	0.515
lev	1.83	0.546
fc	1.62	0.617
roa	1.47	0.680
dif	1.35	0.741
cash	1.29	0.775
fta	1.24	0.806
age	1.21	0.826
top1	1.13	0.885
growth	1.11	0.901
soe	1.09	0.917
Mean VIF	1.39	

4.3. Regression Analysis

4.3.1. The Impact of Fintech Adoption on Financing Efficiency

Table 5 reports the regression results for the direct effect of fintech adoption on financing efficiency. Column (1) of the table shows that when only the core explanatory variable is included and year and industry fixed effects are controlled, the coefficient of *FTA* is 0.041 and is significantly positive at the 1 percent level. After all control variables are introduced, column (2) shows that the coefficient of *FTA* remains significantly positive at the 1 percent level with a value of 0.028. Given that the standard deviation of *FTA* is 1.086, a one standard deviation increase in adoption raises financing efficiency by roughly 0.030 units, which is about 4.9 percent of the sample mean. A direct positive effect of fintech adoption on financing efficiency is therefore established and H1 is supported. Among the control variables, firm size and operating cash flow carry significantly positive coefficients while leverage carries a significantly negative coefficient. This is consistent with the expectation that larger and more liquid enterprises face fewer frictions in the financing process, whereas a heavy debt burden absorbs financing input without generating a matching output.

Table 5. Main Effect Regression Results

Variable	(1) fe	(2) fe
fta	0.041*** (5.126)	0.028*** (3.874)
size		0.036*** (9.412)
lev		-0.147*** (-8.226)
roa		0.482*** (12.735)
growth		0.061*** (6.548)
age		-0.029*** (-3.317)
cash		0.213*** (5.904)
top1		0.001** (2.146)
soe		-0.014 (-1.238)
_cons	0.553*** (48.217)	-0.174** (-2.372)
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
N	15432	15432
R-squared	0.038	0.246
F	26.281	187.463

Note: *** p<0.01, ** p<0.05, * p<0.1. Values in parentheses are t statistics.

4.3.2. Mediating Effect Analysis of Financing Constraints

Table 6 reports the mediating effect test. Column (2) shows that the coefficient of *FTA* on financing constraints is -0.036 and is significant at the 1 percent level, which indicates that enterprises with more intensive fintech adoption face measurably looser financing constraints and H2 is supported. Column (3) introduces the mediating variable into the efficiency equation. The coefficient of *FC* is -0.238 and is significant at the 1 percent level, confirming that a tighter constraint depresses financing efficiency. The coefficient of *FTA* falls from 0.028 in column (1) to 0.019 in column (3) and remains significant at the 5 percent level. Financing constraints therefore carry part but not all of the effect, so partial mediation is established and H3 is

supported. The indirect effect equals 0.009 and accounts for about 30.6 percent of the total effect, which implies that the relief of capital scarcity is an important channel while a substantial share of the efficiency gain is generated directly through improved matching of the timing and structure of funds.

Table 6. Regression Results of the Mediating Effect

Variable	(1) fe	(2) fc	(3) fe
fta	0.028*** (3.874)	-0.036*** (-6.215)	0.019** (2.437)
fc			-0.238*** (-9.126)
size	0.036*** (9.412)	-0.052*** (-14.308)	0.024*** (6.117)
lev	-0.147*** (-8.226)	0.031*** (3.542)	-0.140*** (-7.813)
roa	0.482*** (12.735)	-0.094*** (-4.716)	0.460*** (12.106)
growth	0.061*** (6.548)	-0.017*** (-3.208)	0.057*** (6.132)
age	-0.029*** (-3.317)	0.118*** (16.472)	-0.001 (-0.104)
cash	0.213*** (5.904)	-0.045** (-2.283)	0.202*** (5.617)
top1	0.001** (2.146)	-0.000 (-0.914)	0.001** (2.048)
soe	-0.014 (-1.238)	0.008 (1.126)	-0.012 (-1.073)
_cons	-0.174** (-2.372)	4.581*** (62.194)	0.916*** (7.428)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
N	15432	15432	15432
R-squared	0.246	0.318	0.271
F	187.463	241.052	196.874

Note: *** p<0.01, ** p<0.05, * p<0.1. Values in parentheses are t statistics.

4.3.3. Moderating Effect Analysis of Digital Inclusive Finance

Table 7. Regression Results of the Moderating Effect

Variable	(1) fe	(2) fe	(3) fe
fta	0.028*** (3.874)	0.026*** (3.612)	0.024*** (3.428)
dif		0.045*** (4.883)	0.039*** (4.216)
fta multiplied by dif			0.017*** (3.052)
Control variables	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
_cons	-0.174** (-2.372)	-0.281*** (-3.615)	-0.263*** (-3.402)
N	15432	15432	15432
R-squared	0.246	0.258	0.263
F	187.463	179.204	172.518

Note: *** p<0.01, ** p<0.05, * p<0.1. Values in parentheses are t statistics.

Table 7 reports the moderating effect test. Column (2) adds the regional index without the interaction term, and the coefficient of DIF is 0.045 and significant at the 1 percent level, which shows that a stronger local digital financial environment raises financing efficiency for every enterprise located in that city. Column (3) adds the interaction between the centred adoption measure and the centred regional index. The interaction coefficient is 0.017 and is significant at the 1 percent level, so the marginal return to adoption rises with the regional level of digital inclusive finance and H4 is supported. A capability held inside the enterprise therefore delivers a larger return where the local financial system has the interfaces and the risk models needed to price the information that capability generates.

Figure 4 plots the simple slope of financing efficiency on fintech adoption at a regional index one standard deviation below the mean and at a regional index one standard deviation above the mean. The upper line is visibly steeper, which gives a graphical expression of the interaction coefficient reported in column (3) of Table 7.

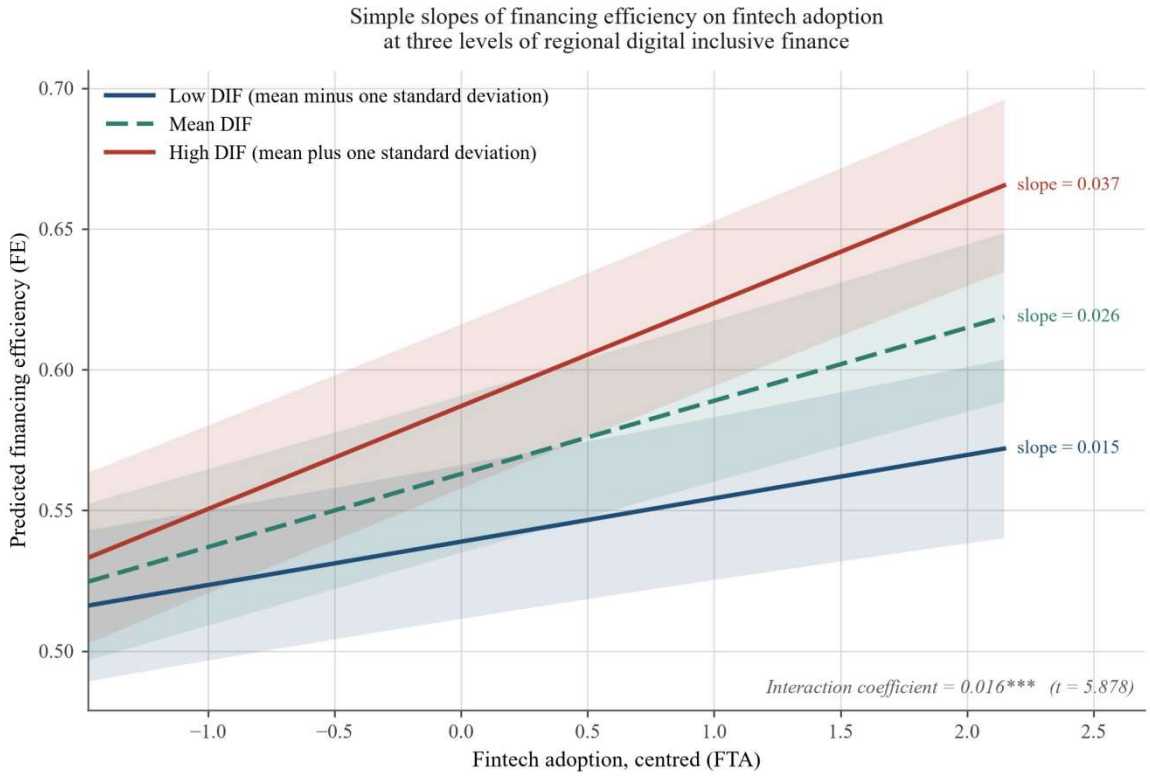


Figure 4. Moderating Effect of Digital Inclusive Finance

4.4. Heterogeneity Analysis

Table 8 presents the heterogeneity test based on ownership. The full sample is split into state controlled and non state controlled enterprises in order to examine differences in the way fintech adoption shapes financing efficiency. In the non state controlled subsample the coefficient of *FTA* is 0.035 and is significant at the 1 percent level, whereas in the state controlled subsample the coefficient falls to 0.012 and does not reach conventional significance. The likely explanation is that state controlled enterprises already enjoy implicit guarantees and preferential access to bank credit, so the information advantage created by digital technology has little residual value for them. Privately controlled enterprises, by contrast, depend on exactly the kind of verifiable operating record that fintech adoption generates.

Table 8. Heterogeneity Analysis of Property Rights

Variable	Non state controlled	State controlled
fta	0.035*** (4.102)	0.012 (1.024)
Control variables	Yes	Yes
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
_cons	-0.208** (-2.541)	-0.096 (-0.782)
N	13164	2268
R-squared	0.239	0.286
F	162.417	41.836

Note: *** p<0.01, ** p<0.05, * p<0.1. Values in parentheses are t statistics.

Table 9 presents the regional heterogeneity test, in which the sample is divided according to whether the registered office of the enterprise lies in the eastern coastal provinces or in the central and western provinces. The coefficient of *FTA* is 0.021 and significant at the 5 percent level in the eastern subsample, and rises to 0.044 with significance at the 1 percent level in the central and western subsample. The larger coefficient inland indicates that fintech adoption serves as a substitute for a thin traditional financial infrastructure. Where bank branch density and relationship lending capacity are already high, the marginal information gain from digital adoption is smaller. This result complements rather than contradicts the moderating effect documented in Table 7. The regional index reflects the digital dimension of local finance, while the east and west division reflects the traditional dimension.

Table 9. Regional Heterogeneity Analysis

Variable	**Eastern region**	**Central and western region**
fta	0.021** (2.213)	0.044*** (4.517)
Control variables	Yes	Yes
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
_cons	-0.152* (-1.874)	-0.237** (-2.406)
N	9873	5559
R-squared	0.252	0.238
F	128.735	74.219

Note: *** p<0.01, ** p<0.05, * p<0.1. Values in parentheses are t statistics.

Source: estimation results of this study.

4.5. Robustness Analysis

4.5.1. Replace the Explained Variable

The super efficiency specification is sensitive to the treatment of slacks, so the explained variable is recomputed with a radial variable returns to scale model applied to the same input and output set, and the resulting score is denoted by *FE2*. Table 10 reports the re estimated main effect. The coefficient of *FTA* is 0.026 and remains significant at the 1 percent level, and

the signs and significance of the control variables are unchanged, which indicates that the conclusion is not an artefact of the efficiency measurement technique.

Table 10. Robustness Test with a Replaced Explained Variable

Variable	(1) fe2	(2) fe2
fta	0.038*** (4.762)	0.026*** (3.512)
Control variables	No	Yes
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
_cons	0.528*** (45.906)	-0.161** (-2.208)
N	15432	15432
R-squared	0.034	0.231
F	23.914	174.628

Note: *** p<0.01, ** p<0.05, * p<0.1. Values in parentheses are t statistics.

4.5.2. One Period Lag Treatment

Reverse causality is a plausible concern, since an enterprise that already finances itself efficiently may have more spare resources to invest in digital technology. To address this concern the core explanatory variable is lagged by one period while the explained variable remains contemporaneous. Table 11 reports the result. The coefficient of the lagged adoption measure is 0.024 and is significant at the 1 percent level, so the estimated relationship survives when current financing efficiency cannot mechanically influence past adoption. Taken together with Table 10, the evidence indicates that the core conclusions of this paper are stable and that endogeneity does not substantially distort the empirical results.

Table 11. Robustness Test with the Core Explanatory Variable Lagged One Period

Variable	(1) fe	(2) fe
L.fta	0.036*** (4.318)	0.024*** (3.208)
Control variables	No	Yes
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
_cons	0.561*** (44.172)	-0.169** (-2.263)
N	13556	13556
R-squared	0.036	0.243
F	22.507	161.379

Note: *** p<0.01, ** p<0.05, * p<0.1. Values in parentheses are t statistics.

5. Research Conclusion

We use enterprises listed on the SME board and the ChiNext board of the Shenzhen Stock Exchange from 2013 to 2023 as the research sample and empirically test the mechanism through which fintech adoption at the level of the individual enterprise shapes financing efficiency. The results show that fintech adoption has a significant positive effect on financing efficiency. Digital technologies embedded in funding, settlement and risk management

activities are converted into a measurable improvement in the ratio of financing output to financing input, and the main effect hypothesis is verified.

At the level of the transmission mechanism, financing constraints partially mediate the association between the two variables. Fintech adoption not only raises financing efficiency directly but also contributes indirectly by loosening the constraint on external capital. The indirect path accounts for roughly three tenths of the total effect. The remaining share is generated directly through better alignment between the timing of fund raising and the timing of expenditure, suggesting that the value of digital technology in the financing process is not exhausted by the volume of credit obtained.

The moderating test shows that the regional level of digital inclusive finance strengthens the effect. The interaction between adoption and the regional index is significantly positive. A capability held inside an enterprise thus delivers a larger return where local financial institutions maintain the data interfaces and the risk pricing models needed to read the information that capability generates. Firm level digital capability and external digital infrastructure are therefore complementary rather than substitutable.

Heterogeneity tests show that ownership nature and regional location generate significant differences in the above effects. The efficiency gain is concentrated among non state controlled enterprises, in which access to bank credit is not supported by implicit guarantees, while the effect in the state controlled subsample does not reach conventional significance. The gain is also larger in central and western provinces than in the eastern coastal provinces, indicating that digital adoption partially substitutes for a thin traditional financial infrastructure. Robustness tests that replace the efficiency measurement technique and that lag the core explanatory variable by one period indicate that the core conclusions are stable.

Several implications follow. Policy support for small and medium sized enterprises should target the capacity of enterprises to adopt digital financial tools rather than only the supply of credit, since adoption is what converts available infrastructure into realised efficiency. Regional programmes should treat digital financial infrastructure and enterprise level digital capability as a package, because the return to either one depends on the presence of the other. Financial institutions in central and western regions stand to gain the most from expanding lending to smaller borrowers through data based credit technology. Two limitations should be acknowledged. Adoption measured from disclosure text reflects strategic emphasis rather than the volume of digital transactions actually executed, and the sample covers listed enterprises only, so the smallest and most opaque borrowers lie outside its scope. Extending the analysis to survey data or to platform transaction records would be a productive direction for further work.

References

[1] Abbasi, K., Alam, A., Brohi, N. A., Brohi, I. A., & Nasim, S. (2021). P2P lending fintechs and SMEs' access to finance. *Economics Letters*, 204, 109890.

[2] Khan, H. H., & Ahmad, M. R. (2025). The fintech revolution: Exploring the potential of fintech finance in reducing corporate credit constraints. *Research in International Business and Finance*, 79, 103033.

[3] Ha, D., Le, P., & Nguyen, D. K. (2025). Financial inclusion and fintech: A state-of-the-art systematic literature review. *Financial Innovation*, 11(1), 69.

[4] Chen, C., Xiao, B., Wang, J., & Ye, H. (2023). The effects of fintech development on financing constraints of small and medium-sized enterprises-Evidence from China. *Managerial and Decision Economics*, 44(7), 4161–4172.

[5] Yang, J., Zhang, Y., Gong, J., & Liu, T. (2024). How does fintech development affect financing constraints of SMEs? Evidence from China. *Economics – Innovative and Economics Research Journal*, 12(3), 1–32.

[6] Li, X., Ye, Y., Liu, Z., Tao, Y., & Jiang, J. (2024). FinTech and SME' performance: Evidence from China. *Economic Analysis and Policy*, 81, 670–682.

[7] Li, Y., Chu, E., Nie, S., Peng, X., & Yi, Y. (2024). Fintech, financing constraints and corporate green innovation. *International Review of Financial Analysis*, 96, 103650.

[8] Fan, C., Bae, S., & Liu, Y. (2024). Can FinTech transform corporate liquidity? Evidence from China. *Innovation and Green Development*, 3(2), 100114.

[9] Bu, Y., Du, X., Wang, Y., Liu, S., Tang, M., & Li, H. (2024). Digital inclusive finance: A lever for SME financing? *International Review of Financial Analysis*, 93, 103115.

[10] Zhang, X., Li, J., Xiang, D., & Worthington, A. C. (2023). Digitalization, financial inclusion, and small and medium-sized enterprise financing: Evidence from China. *Economic Modelling*, 126, 106410.

[11] Li, W., & Pang, W. (2023). Digital inclusive finance, financial mismatch and the innovation capacity of small and medium-sized enterprises: Evidence from Chinese listed companies. *Heliyon*, 9(2), e13792.

[12] Gu, F., Gao, J., Zhu, X., & Ye, J. (2023). The impact of digital inclusive finance on SMEs' technological innovation activities-Empirical analysis based on the data of new third board enterprises. *PLOS ONE*, 18(11), e0293500.

[13] Lee, C.-C., Tang, M., & Lee, C.-C. (2023). Reaping digital dividends: Digital inclusive finance and high-quality development of enterprises in China. *Telecommunications Policy*, 47(2), 102484.

[14] Su, R., Zheng, T., Zhong, Y., & Zhong, W. (2023). Role of digital inclusive finance for high-quality business development: A study of China's "Five Development Concept" Policy. *Sustainability*, 15(15), 12078.

[15] Sheng, T. (2021). The effect of fintech on banks' credit provision to SMEs: Evidence from China. *Finance Research Letters*, 39, 101558.

[16] Feng, J., Jiao, W., & Wang, Y. (2025). Bank fintech and lending distance: The role of information asymmetry and risk management channels. *Economic Modelling*, 151, 107154.

[17] Yang, N., Zang, R., Yin, C., & Liu, G. (2026). Digital transformation and the inclusive financial efficiency for small and micro enterprises: Evidence from Chinese commercial banks. *Humanities and Social Sciences Communications*.

[18] Guan, Y., Sun, N., Wu, S. J., & Sun, Y. (2025). Supply chain finance, fintech development, and financing efficiency of SMEs in China. *Administrative Sciences*, 15(3), 86.

[19] Xu, W., Zhang, M., & Wang, F. (2023). Financing efficiency and influencing factors of high-tech small and medium-sized enterprises of information technology industry in the China Yangtze River Delta. *SAGE Open*, 13(4), 1–16.

[20] Liu, H., & Fu, Z. (2024). Supply chain finance and financing efficiency of technology-based SMEs. *Applied Mathematics and Nonlinear Sciences*, 9(1), 1–16.

[21] Yang, T., & Zhang, X. (2022). FinTech adoption and financial inclusion: Evidence from household consumption in China. *Journal of Banking & Finance*, 145, 106668.

[22] Xu, T., Shen, Z., Zhang, H., Zhang, C., & Huang, H. (2024). Digital HP finance's role in the economic resilience of enterprises' digital transformation. *Finance Research Letters*, 63, 105312.

[23] Tang, M., Hou, Y. (G.), Goodell, J. W., & Hu, Y. (2024). Fintech and corporate risk-taking: Evidence from China. *Finance Research Letters*, 64, 105411.

[24] Tone, K. (2002). A slacks-based measure of super-efficiency in data envelopment analysis. *European Journal of Operational Research*, 143(1), 32–41.

[25] Guo, F., & Wang, J. (2022). Quantifying digital financial inclusion in China. In D. Dollar & Y. Huang (Eds.), *The digital financial revolution in China* (pp. 17–44). Brookings Institution Press.

[26] Stiglitz, J. E., & Weiss, A. (1981). Credit rationing in markets with imperfect information. *American Economic Review*, 71(3), 393–410.

[27] Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 13(2), 187–221.

[28] Hadlock, C. J., & Pierce, J. R. (2010). New evidence on measuring financial constraints: Moving beyond the KZ index. *Review of Financial Studies*, 23(5), 1909–1940.

[29] 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, 1–21.