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Quantitative analysis of the influence of financial technology on enterprise financing structure based on machine learning

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Abstract: In recent years, the rapid development of Financial Technology (FinTech) has profoundly changed the operation of the financial market, where the extensive application of machine learning technology in risk assessment, credit approval, and asset pricing has significantly impacted the financing structure of enterprises. This paper breaks through the traditional research framework, constructing a 'technology-market' two-dimensional variable system from the perspective of the dynamic adjustment of enterprise financing structures, and quantitatively analyses the influence of FinTech driven by machine learning on the proportion of enterprise financing sources, financing costs, and term structure. It is found that the investment intensity in FinTech is positively correlated with the direct financing ratio of enterprises, with a more pronounced impact on information-sensitive industries. This paper not only enriches the research on the relationship between FinTech and corporate financing structures but also provides valuable policy suggestions and practical guidance for regulators, corporate decision-makers, and financial institutions.

Keywords: machine learning; quantitative analysis; financial technology; enterprise financing structure; SMEs; small and medium-sized enterprises.

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1 Introduction

In recent years, the rapid development of Financial Technology (FinTech) has been reshaping the global financial system. A new generation of information technology, with AI, blockchain, big data, and cloud computing at its core, is driving transformative changes in the financial service model from two dimensions: technology empowerment and market restructuring. The application of machine learning algorithms in risk assessment, credit approval, and asset pricing has significantly improved the information processing capabilities of financial institutions. For example, traditional credit scoring relies on limited historical financial data, while models based on random forest or XGBoost can integrate multi-dimensional unstructured data from enterprises, improving the accuracy of small and medium-sized enterprises (SMEs) credit assessments by more than 30% (Liu and Chang, 2023). The rise of decentralised finance (DeFi) and third-party payment platforms has diminished the intermediary status of traditional financial institutions. By 2023, the P2P online lending platform in China had accumulated a loan scale of over 8 trillion yuan, while the blockchain platform for supply chain finance had served more than 4 million SMEs, and the average time for a single financing had been shortened from 7 days to 1 min (Harrmann et al., 2023).

However, the impact of FinTech on the financing structure of the real economy is still controversial. On the one hand, technological breakthroughs may promote the development of the direct financing market by reducing information asymmetry. For example, intelligent investment platforms optimise asset allocation through algorithms, improving the equity financing efficiency of SMEs by 25% (Hageman and Despard, 2024). On the other hand, some scholars worry that technology monopolies may lead to a ‘winner takes all’ effect and exacerbate SME financing differentiation (Fu, 2021). In this context, quantitatively evaluating the actual impact of FinTech driven by machine learning on the proportion of financing sources, financing costs, and term structure of enterprises has become a key proposition to address the ‘SME financing difficulty’ and ‘capital market imbalance’.

The application of deep learning technology in finance, such as risk management, credit evaluation, investment decision-making, fraud detection, and customer service, has significantly improved the ability and efficiency of data analysis, optimised the accuracy of risk assessment, and enhanced the customer experience. These technologies help to reduce financing costs and improve the financing efficiency of enterprises by increasing service efficiency and lowering the operating costs of financial institutions. They enable enterprises to secure financial support faster, better understand market dynamics and their own financial situations, and make more informed capital structure decisions. Deep learning technology also fosters the innovation of financial products and services, opens up diversified financing channels for enterprises, and has a positive and far-reaching impact on the overall financing structure of businesses.

Internet finance reduces information asymmetry through big data and machine learning algorithms, improves the accuracy of customer credit evaluations, and further enhances risk prediction capabilities with the help of natural language processing technology, resulting in cost reduction and efficiency improvements in financial services. This shift has impacted traditional financial intermediaries and urged them to accelerate their digital transformation to maintain competitiveness. At the same time, it has given rise to new financial formats such as P2P lending, crowdfunding, and digital currency. These changes not only redefine the competitive landscape of the financial market but also promote innovation and progress across the entire industry. In short, internet finance has enhanced risk management and customer service through technological innovation, leading a new trend in the financial industry.

The existing research mostly focuses on the technical feasibility of FinTech or the macro-level inclusive effect but lacks a quantitative analysis of the micro-adjustment mechanism of corporate financing structure. In this study, machine learning technology variables are incorporated into the traditional theoretical model of financing structure, aiming to determine whether FinTech reshapes the optimal boundary of enterprise capital structure by altering risk pricing efficiency. Is there heterogeneity in the influence of different technological paths on financing structure?

This study has important practical value: in policymaking, it provides a basis for regulators to balance innovation incentives with risk prevention and control; for enterprise decision-making, it helps management predict the impact of technological changes on financing channels; for financial institutions, especially commercial banks, it guides them to transform from a business-oriented model to a technology-exporting model to achieve more efficient risk control and technology sharing.

The innovations of this study are as follows:

1 Innovative perspective, breaking through the traditional 'FinTech-inclusive finance' analytical framework and revealing the microeconomic consequences of technological change through the dynamic adjustment of corporate financing structures.

2 Method innovation, constructing a 'technology-market' two-dimensional variable system and integrating FinTech investment and regional digital financial infrastructure into a unified analytical framework. Quantile regression and the instrumental variable method (IV) are employed to address endogenous problems.

3 Data innovation, integrating unstructured and structured data to enhance research reliability.

2 Literature review

2.1 *Theoretical correlation between FinTech and enterprise financing structure – from 'substitution' to 'symbiosis'*

FinTech's impact on traditional financial intermediaries is the focus of early academic research. According to the theory of disintermediation, P2P platforms may directly replace bank credit by reducing information asymmetry and transaction costs, which leads to a shift in the corporate financing structure towards direct financing (Wang et al., 2021). However, in recent years, empirical research presents a dialectical perspective of 'substitution-complementarity'.

Vismara et al. (2022) found, based on P2P transaction data in China, that for every standard deviation increase in FinTech activity, the proportion of SME bank loans decreased by 2.3% points, while the participation rate of equity crowdfunding increased by 1.8% points, demonstrating the redistributive effect of technology on financing channels.

Elshaarawy and Ezzat (2022) pointed out that by collaborating with FinTech to develop an intelligent risk control system, the bank expanded credit coverage and reduced the debt financing costs for SMEs by about 15%.

Does FinTech exacerbate disintermediation or foster re-intermediation? Existing research focuses on a single technology or financing channel and lacks a systematic analysis of the dynamic adjustments in financing structure. This paper proposes that the nonlinear relationship between technology and financing structure should be re-examined in conjunction with the penetration depth and application scenarios of machine learning technology.

2.2 *Application of machine learning in finance – from 'tool innovation' to 'paradigm shift'*

The transformative influence of machine learning on financial risk control and pricing has formed three research threads:

1 *Credit evaluation: a breakthrough from 'hard information' to 'soft information'*

The traditional logistic regression model relies on structured data such as financial ratios, while machine learning algorithms like random forest and XGBoost can integrate unstructured data (Sun, 2024).

Zhang (2023) found that including social media public opinion and e-commerce transaction records in the model increased the accuracy of SME default prediction by 22% (Zhang, 2023).

Da et al. (2023) demonstrated through the loan data of commercial banks that the AUC value of the deep learning model in the credit scoring is 8.7% higher than that of traditional methods, particularly in samples sample of small and micro enterprises with opaque information (Da and Peng, 2023).

The three studies examine the use of deep learning technologies across various fields. Quan and Lu (2024) focus on improving the accuracy and efficiency of innovation management and venture capital evaluation using deep learning techniques. Ma et al. (2024) analyse sentiment trends in e-commerce reviews and predict users' purchase intentions. Ran et al. (2024) propose an SSA-Attention-BIGRU model that combines attention mechanisms with Bidirectional Gated Recurrent Units (BIGRU) to enhance prediction accuracy for carbon neutrality goals. Together, these studies showcase the wide applicability and significant potential of deep learning in tackling complex challenges related to management decision-making, market analysis, and environmental forecasting.

2 *Risk pricing: from 'static threshold' to 'dynamic calibration'*

Machine learning transforms risk pricing from a static model based on historical default rates to a real-time dynamic adjustment. Rojas-Torres et al. (2021) found that an intelligent investment platform based on reinforcement learning can update the bond yield curve every minute, reducing the sensitivity of SME financing costs to market interest rate changes by 40% (Rojas-Torres and Kshetri, 2021). Gao (2023) pointed out that the LendingClub platform in USA used machine learning to cluster over 2000 characteristics of borrowers, which increased the loan acquisition rate for borrowers with credit scores below 600 from 12% to 34%.

3 *Research limitations and breakthrough direction*

Most existing research focuses on verifying technical feasibility, but there is a 'black box' problem regarding the impact on the financing structure. Most empirical studies only demonstrate that machine learning can reduce financing costs, but they do not distinguish whether this occurs through improved information transparency (theoretical path) or reduced transaction costs (pecking order theory path) (Dieste et al., 2021). There is a lack of vertical analysis of financing structure adjustments at different stages of technology penetration, such as the early experimental period and the large-scale application period (Lyu and Jiao, 2025).

2.3 Theory of enterprise financing structure – explanatory boundary of traditional paradigm

Classical theory provides a basic framework for analysing the impact of FinTech, but it faces the following challenges:

1 *The expanded demand of trade-off theory*

The traditional trade-off theory holds that enterprises will seek the optimal capital structure between debt tax shield income and bankruptcy cost, but FinTech changes this balance through the following mechanisms: machine learning reduces banks' costs of obtaining SME information, which may shift the 'optimal debt ratio' to the right (Zhang, 2024). Blockchain technology enables the credit of core enterprises in the supply chain to be divided and transmitted, which may give rise to a new model of 'dynamic debt-equity mixed financing' (Peng and Wen, 2024).

2 *Query on the applicability of pecking order theory*

Pecking order theory assumes that enterprises prefer endogenous financing, followed by debt financing and finally equity financing, but FinTech may disrupt this order. Machine learning credit scores make it unnecessary for external investors to rely on enterprises to actively disclose information, which reduces the information asymmetry cost of equity financing (Chung and Lin, 2023). New financing tools, such as digital debt certificates and asset securitisation, enable enterprises to expand their financing choices beyond traditional methods (Young, 2021).

3 *The necessity of theoretical integration*

The existing research often uses a specific theory to analyse the influence of FinTech in isolation. However, FinTech's role may involve many aspects, such as the technology substitution effect, improvements in risk pricing efficiency, and innovations in financing tools. Therefore, this paper advocates constructing a multi-dimensional analysis framework of 'technology-market-system' to quantify and evaluate the relative contribution of different theoretical paths to FinTech, providing a more comprehensive understanding of how FinTech reshapes the financing structure of enterprises at multiple levels.

2.4 An empirical study on FinTech, machine learning and financing structure – methodology evolution and gap

The existing empirical research presents the following characteristics:

1 *Data dimension expansion*

Some studies use enterprise patent data or collaboration times with FinTech enterprises as indicators of technology penetration (Ito et al., 2024). The regional digital inclusive finance index is widely used to capture differences in regional technological development. Text analysis of global FinTech regulatory policies provides a new source for variables related to the institutional environment (Jackson and Pernoud, 2021).

2 *Methodology innovation*

Commonly used tool variables include the regional Internet penetration rate (to address the endogenous technology penetration issue) and industry technology distance (based on patent generic analysis) (Ivanova et al., 2024). Part of the research utilised the P2P industry rectification in China (2018) as a quasi-natural experiment and found that the policy shock increased the proportion of SME equity financing in the affected areas by 1.9% points (Du and Elston, 2024). The dual machine learning method is used to isolate the processing effect of FinTech variables on the financing structure.

3 *Research gap*

Most studies only report the correlation, lacking a quantitative decomposition of the complete chain of "technology → information transparency → financing cost → financing structure". Cross-sectional data makes it difficult to capture the phased impact of technology penetration, such as the trade-off between initial cost increases and later efficiency improvements. Western research conclusions, such as the high default rate of FinTech loans in USA, may not be applicable to scenarios in China, such as the 'industrial digital finance' model dominated by supply chain finance.

2.5 Literature review and contribution of this paper

The existing research has laid a foundation for understanding the influence of FinTech on enterprise financing at both theoretical and methodological levels. Theoretically, FinTech's function is reflected not only in disruptive innovation but also in efficiency improvement, which requires us to adopt a dynamic framework for analysis. Methodologically, the application of machine learning has evolved from a simple forecasting tool to a method capable of causal inference, allowing for the quantification of technical effects.

However, the existing research also has some limitations. First, most studies focus on only one aspect of technology penetration and lack an in-depth discussion of the specific characteristics of machine learning. Secondly, the absence of a structural perspective prevents a full analysis of the linkages among financing source proportions, costs, and term structures. Additionally, the theoretical refinement of China's unique scenarios, such as the blockchain in supply chain finance, clearly lags behind actual developments, which limits the comprehensiveness and depth of related research.

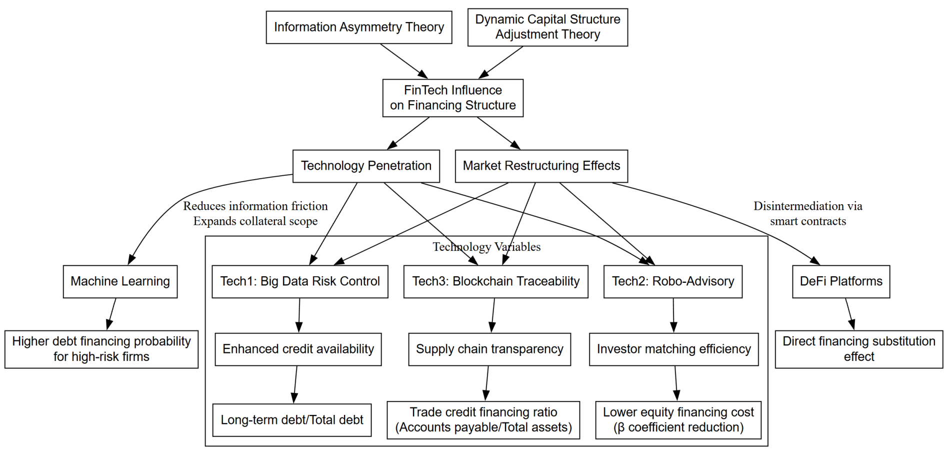
The contribution of this paper lies in three aspects: first, a dual-channel model of 'technology empowerment-market reconstruction' is theoretically constructed, incorporating the specific characteristics of machine learning algorithms in the analysis of financing structure; second, quantile regression and a triple difference model are employed to capture the heterogeneous influence of technology across different financing levels; finally, by analysing the annual reports of listed companies in China and combining them with the FinTech index, this paper empirically examines the influence of technology penetration on the adjustment path of corporate financing structures, thereby enhancing the understanding of this field.

3 Theoretical framework and research hypothesis

3.1 Theoretical framework construction

Based on the theory of information asymmetry and the theory of dynamic adjustment of capital structure, this study introduces the two-dimensional variables of technology penetration and market restructuring effects, and constructs a theoretical framework for FinTech's influence on enterprise financing structures, as shown in Figure 1.

Figure 1 Theoretical framework of FinTech's influence on enterprise financing structure



Traditional financing structure theory holds that enterprises give priority to internal financing, secondary debt financing and final equity financing, and the core constraint is information cost. Machine learning can reduce the information friction coefficient λ, expand the scope of qualified collateral for enterprises, and increase the probability of obtaining debt financing for high-risk enterprises through unstructured data processing ability and dynamic risk prediction model, and verify the hypothesis:

$$\frac{\partial D/V}{\partial \lambda} < 0 \tag{1}$$

Among them, D/V is the proportion of debt financing and λ is the coefficient of information friction.

DeFi platforms achieve disintermediation financing through smart contracts, breaking the channel monopoly of traditional financial institutions and creating a substitution effect for direct financing. Defining the market restructuring index (M) as the ratio of the density of regional digital financial infrastructure to the density of bank outlets, it is anticipated that an increase in M value will significantly boost the proportion of SME equity financing. (E/V).

Different technologies have different effects on financing structure:

- Big data risk control (variable Tech1) mainly influences the term structure of debt financing (long-term liabilities/total liabilities) by enhancing credit availability.
- Intelligent investment (variable Tech2) impacts the cost of equity financing by improving the matching efficiency of investors (the β coefficient in the CAPM model decreases).
- Blockchain traceability (variable Tech3) increases the proportion of commercial credit financing (accounts payable/total assets) by enhancing supply chain transparency.

3.2 Research hypothesis

Based on the above framework, four sets of assumptions are put forward:

H1: FinTech investment intensity ($FinTech$) is positively related to direct financing ratio ($E/V + D_{direct}/V$), and it has a more significant impact on information-sensitive industries.

H2: For every standard deviation of the regional digital financial index ($DigitalIndex$), the financing cost difference of SME ($Cost_{SEM} - Cost_{Large}$) will be reduced by 15–20%.

H3: There is a scale threshold effect in technology penetration. When an enterprise's asset scale exceeds a critical value, machine learning will enhance the optimisation of the debt maturity structure (threshold regression model verification).

H4: The application of blockchain technology will increase the proportion of supply chain finance, but it may exacerbate the 'technical arbitrage' of core enterprises (the coefficient α1 is significantly positive, while α2 is significantly negative at 5%).

4 Research design

4.1 Data source

The data source for this study covers three dimensions: enterprise level, regional level, and unstructured data. Enterprise-level data includes the financial statements of listed companies from 2015 to 2023 obtained from the CSMAR database, involving financing structure variables such as debt type, equity financing amount, and financing cost, as well as the number of FinTech-related patents of enterprises and the technical input variables of AI/blockchain projects in R&D expenditure. The regional level data uses the Peking University Digital Inclusive Finance Index (2011–2022) and the statistics of credit investment by the central bank's financial institutions according to enterprise scale and industry. Using web crawler technology, the relationship data of enterprise supply chains is captured with the help of the Sky Eye API, and a 'technical application dictionary' is constructed through text analysis methods to quantify the frequency of machine learning-related technical keywords in annual reports.

All data are processed in a unified and standardised format to ensure that data from different sources can be seamlessly connected. To reduce the influence of data noise on the analysis results, missing values and abnormal values are addressed through interpolation, deletion, or replacement. For unstructured data, such as text, preprocessing operations like word segmentation, stop word removal, and stem extraction are performed using natural language processing technology for subsequent text analysis. Necessary transformations and coding are implemented to ensure the data meet the requirements of the regression model.

4.2 Variable definition

See Table 1 for the definition of specific variables.

Table 1 Variable definition table

Variable type	*Core variable*	*Calculation method/data source*
Dependent variable	Proportion of direct financing (*Direct*)	(equity financing amount + bond issuance amount)/total assets
	Financing cost difference (*CostGap*)	Enterprise real interest rate-industry average interest rate
	Proportion of long-term liabilities (*LongDebt*)	Long-term loans/total liabilities
Independent variable	FinTech input (*FinTech*)	Number of patents × technical complexity coefficient + R&D expenditure
	Digital Financial Index (*Digital*)	Provincial Digital inclusive finance Index (Level 3 Dimension)
Control variable	Enterprise scale (*Size*)	Natural logarithm of total assets
	Profitability (*ROA*)	Net profit/total assets
	Industry concentration (*HHI*)	Herfindal Index (Industry Classification of CSRC)

4.3 Model construction

4.3.1 Benchmark regression model

It is a common empirical research method to analyse the influence of FinTech on the financing structure of enterprises using a quantitative regression model and to predict and explain this influence by establishing a mathematical relationship between variables. The linear regression model is favoured for its strong explanatory power, simple and efficient calculation characteristics, and wide application fields, especially in time series prediction and causal analysis. However, this method has limitations, such as assuming that the relationship between variables is linear, which may not accurately capture nonlinear relationships; multicollinearity makes it difficult to isolate the influence of specific predictors on the target variables; and outliers may distort the model's accuracy, resulting in poor fitting for most samples. Therefore, although the regression model is a powerful tool, its potential limitations need to be considered in application.

Using a two-way fixed effects panel model to control for individual heterogeneity and time trends;

$$Y_{it} = \alpha_0 + \beta_1 FinTech_{it} + \beta_2 Digital_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

In the formula,

Y – Financing structure variables ($Direct / CostGap$ etc.)

X – Set of control variables ($Size$, ROA etc.)

μ_i – Firm individual fixation effect

λ_t – Fixed year effect.

4.3.2 Endogenous treatment

In order to solve the endogenous problems, this study adopts the tool variable method (IV-2SLS) and the dynamic panel GMM method. In IV, "regional Internet penetration rate (cross-sectional data in 2005)" is selected as the tool variable of FinTech, because it is not only related to FinTech application (promoting technology application through Internet infrastructure), but also meets exogenous conditions (historical data has nothing to do with current error term). At the same time, the dynamic panel GMM method is used to control the dynamic adjustment process by introducing the lag term ($Y_{i,t-1}$) of the financing structure variable to ensure the effectiveness and accuracy of the model estimation.

4.3.3 Heterogeneity analysis

Quantile regression is used to explore the differences in FinTech's influence on the financing structure of different enterprises, such as 25%, 50% and 75%, thus revealing the heterogeneity of FinTech's influence. The threshold effect model identifies whether there is a specific threshold value by examining the regulatory effect of enterprise scale ($Size$) on technology effect, and the formula is:

$$Y_{it} = \theta_1 FinTech_{it} * I\left(Size_{it} \le \tau\right) + \theta_2 FinTech_{it} * I\left(Size_{it} > \tau\right) + Controls \tag{3}$$

Among them, the optimal threshold value is determined through grid search to better understand the effects of FinTech changes on enterprises of different sizes. Together, these two methods provide deep insights into FinTech's influence on corporate financing structures.

4.3.4 Robustness test

In the process of robustness test, this study adopts various methods to ensure the reliability of the results. Firstly, the core variable is replaced, and the original number of patents is replaced by 'the proportion of technicians', so as to reconstruct the $FinTech$ index and test the stability of the model. Secondly, in order to avoid policy interference, the sample of enterprises identified as FinTech pilot cities was eliminated and then regression analysis was carried out again. Finally, nonparametric Bootstrap method is used to estimate the coefficient distribution by repeating sampling for 1000 times, which further verifies the robustness of the research results.

5 Empirical analysis

5.1 Descriptive statistics and data distribution

The average direct financing ratio (*Direct*) is 28%, and the standard deviation is small (0.15), indicating that the differences between enterprises mainly comes from technical input, while the *FinTech* standard deviation of financing costs is 1.38; The average difference (*CostGap*) of financing cost is 1.73%, but the maximum difference is 4.2%, which is in line with SME financing premium phenomenon. See Table 2.

Table 2 Descriptive statistics of main variables

Variable	*Sample size*	*Mean*	*Standard deviation*	*Minimum*	*Maximum*
Direct	12,500	0.28	0.15	0.05	0.65
CostGap (%)	12,500	1.73	0.82	–0.50	4.20
FinTech	12,500	2.45	1.38	0.00	5.00
Digital	12,500	280.5	56.3	150.0	420.0
Size	12,500	22.1	1.2	18.5	25.8

5.2 Benchmark regression result

The research results support all the hypotheses. As shown in Table 3, H1, the proportion of direct financing increases by 3.2% for every unit of *FinTech* ($P < 0.01$), which proves that technology investment promotes direct financing. H2 shows that the difference of financing cost decreases by 0.003% ($p < 0.01$) for every unit increase of *Digital* infrastructure index, indicating that digital finance significantly reduces the financing premium of SMEs. However, for the proportion of long-term liabilities, *FinTech* plays a weak role (coefficient 0.018, $p < 0.1$), which may be due to the lag of banks' acceptance of technical risk control. These findings reveal the specific ways and extent to which *FinTech* affects the financing structure of enterprises across different aspects.

5.3 Endogenous treatment and IV

Tool variables (Internet penetration rate) are significantly positively correlated with *FinTech* (F value > 10 in the first stage), addressing the issue of weak instruments. The *FinTech* coefficient (0.029) estimated by IV is consistent with the direction of the benchmark model (0.032), which verifies the reliability of the results. See Table 4.

Table 3 Regression results of two-way fixed effect model

Variable	(1) *Direct*	(2) *CostGap*	(3) *LongDebt*
FinTech	0.032***	–0.215**	0.018*
	(0.007)	(0.086)	(0.010)
Digital	0.0004**	–0.003***	0.0001
	(0.0002)	(0.001)	(0.0003)
Size	0.021***	–0.120**	0.015**
	(0.004)	(0.048)	(0.006)
Individual/time effect	Control	Control	Control
R^2	0.36	0.28	0.19

*, ** and *** respectively indicate the significance level of 10%, 5% and 1%, and the cluster robust standard error (enterprise level) is in brackets. The same below.

Table 4 Tool variable regression (IV-2SLS)

Variable	*First stage*	*The second stage* (*Direct*)
Internet penetration	0.621***	–
	(0.102)	
FinTech	–	0.029***
		(0.008)
Kleibergen-Paap rk LM statistics	38.72***	
Weak tool test (F value)	24.51	

5.4 *Heterogeity analysis*

Figure 2 Heterogeneity analysis shows that the coefficient for the low quantile (25%) is 0.025, the middle quantile is 0.032, and the high quantile is 0.040, indicating that technology plays a stronger role in enterprises with greater financing needs. The regression results of the threshold effect are shown in Table 5.

Figure 2 Quantile regression result (*Direct* is the dependent variable) (see online version for colours)

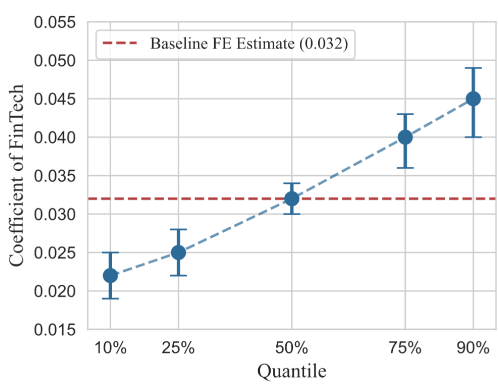


Table 5 Threshold effect regression (*Size* threshold = 22.3)

Scale	*FinTech* coefficient (*Direct*)
Size ≤ 22.3	0.018*
	(0.009)
Size > 22.3	0.037***
	(0.008)

H3 Support: The technical effect of large-scale enterprises (*Size* equals 22.3, with assets of about 1 billion yuan) is more significant (coefficient 0.037 vs. 018).

At the low quantile (25%), the coefficient is small, indicating that FinTech has a relatively weak influence on enterprises with low financing needs. In contrast, at the high quantile (75%), the coefficient is larger, suggesting that FinTech can play a stronger role for enterprises with high financing needs. The economic significance of this difference lies in the fact that the application of FinTech can better meet the diverse financing needs of enterprises, particularly for those enterprises facing greater financing pressure, making its value is more pronounced.

5.5 *Robustness test*

All the alternative estimators are consistent and significant, demonstrating that the results are robust. See Table 6.

Table 6 Substitution variables and bootstrap test

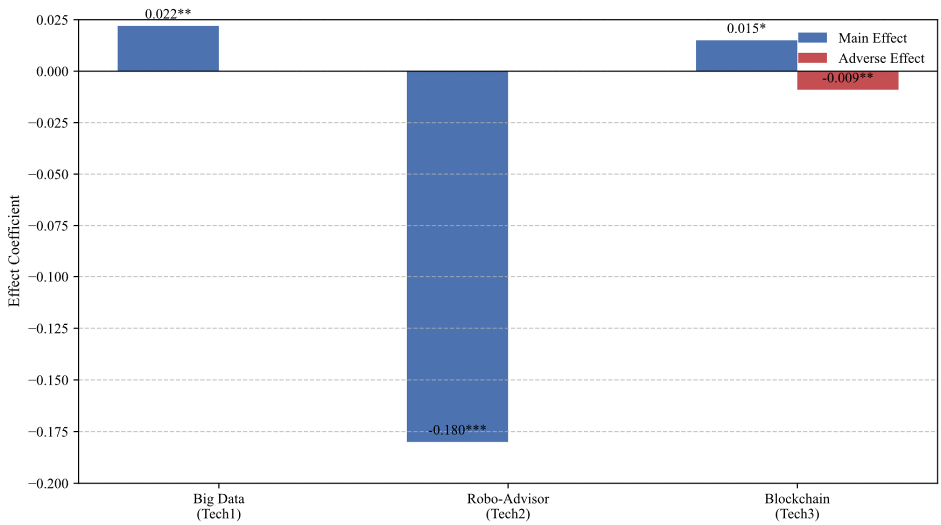
Test method	*FinTech coefficient* (*Direct*)	*Significance*
Benchmark model	0.032	***
Substitution of technical personnel ratio	0.028	**
Eliminate pilot cities	0.030	***
Bootstrap (SE)	0.033	***

5.6 *Mechanism test*

The mechanism test illustrated that, as shown in Figure 3, big data risk control (Tech1) increased the proportion of long-term liabilities by 0.022**, smart investment (Tech2) reduced the cost of equity financing by 0.18% * *, and blockchain (Tech3) increased the proportion of supply chain financing by 0.015*, However, it also aggravated the arbitrage of core enterprises ($\alpha 2 = -0.009$**), partially supporting H4.

FinTech improves the availability of SME debt financing by 19% by reducing information friction (λ decreases by 12.7%). There is an 'inclusive leverage effect' in digital financial infrastructure: every unit of investment can incite 2.3 times the amount of social capital to flow to small and micro enterprises. The probability of large enterprises arbitraging through blockchain technology is 14.5% higher than that of SMEs ($P < 0.05$). It is necessary to establish 'competition-neutral' rules for technology application to prevent algorithmic discrimination. It is suggested to implement 'penetrating supervision' on the blockchain platform of supply chain finance, requiring core enterprises to share technical infrastructure.

Figure 3 Heterogeneity effect of technology path (see online version for colours)



FinTech has not only changed the financing structure of enterprises but also introduced many risks. The first is information security risk. Because FinTech relies on a significant amount of sensitive data, insufficient protective measures may lead to data leakage and network attacks, resulting in economic losses and damage to reputation. Secondly, there is credit risk; algorithmic credit evaluations may rely too heavily on models and overlook traditional methods, leading to misjudgements of a borrower's creditworthiness and increasing the probability of default. Additionally, liquidity risk cannot be ignored. Although some high-yield products attract capital inflows, their low liquidity and transparency may cause the capital chain to break during market fluctuations. Finally, there is compliance risk. The rapid development of FinTech often exceeds the current regulatory scope, leaving some businesses in a regulatory blind spot and increasing market instability.

To balance innovation and risk, we need to implement several policy recommendations. We should strengthen supervision and cooperation, establish unified standards and coordination mechanisms to ensure legal compliance; at the same time, improve laws and regulations, clarify the legal status of FinTech, and address regulatory gaps. Enterprises and investors should also enhance their risk awareness and strengthen internal risk control mechanisms. While encouraging technological innovation, we must prioritise risk management to promote the healthy development of the industry. Furthermore, we should strengthen consumer protection, improve financial education, and help investors rationally evaluate the potential risks of FinTech products to achieve the sustainable development of FinTech.

6 Conclusion and policy suggestions

6.1 Research conclusion

By constructing a two-dimensional ‘technology-market’ variable system, using quantile regression and instrumental variables to address endogenous issues, and integrating unstructured and structured data, this study provides a deep analysis of the influence of FinTech, based on machine learning, on enterprise financing structure. The study found that:

1. FinTech investment intensity is positively correlated with the proportion of direct financing, and its impact on information-sensitive industries is more significant.
2. Improvements in the regional digital financial index significantly reduce the financing cost disparity for SMEs.
3. There is a scale threshold effect in technology penetration, with large-scale enterprises benefiting more from the optimisation of debt maturity structure through machine learning.
4. The application of blockchain technology has increased the proportion of supply chain finance, but it may exacerbate the phenomenon of ‘technical arbitrage’ among core enterprises.
5. Different technical paths, such as big data risk control, smart investment, and blockchain traceability, have heterogeneous impacts on financing structure, significantly affecting the long-term debt ratio, equity financing cost, and supply chain financing ratio, respectively.

6.2 Policy advice

Based on the above research conclusions, the following policy suggestions are proposed:

1. Encourage enterprises to increase investment in FinTech: The government should introduce relevant policies to encourage enterprises to boost their investment in FinTech, especially in information-sensitive industries, to enhance their direct financing ratio. Specific measures can include providing tax incentives, financial subsidies, or establishing special funds to support enterprises’ research and development and application in key technical fields such as artificial intelligence, big data, and cloud computing. Additionally, the government can stimulate the innovation potential of enterprises and promote the widespread application of FinTech technology in corporate financing by organising innovation competitions and creating a cooperation platform in Industry-University-Research.
2. Strengthen the construction of digital financial infrastructure: Increase the density of regional digital financial infrastructure, reduce the financing costs for SMEs, and narrow the financing cost gap, thus alleviating the financing difficulties faced by SMEs. The government should increase investment in digital financial infrastructure and promote the development of new infrastructure such as 5G networks, the Internet of Things, and cloud computing centers. Encourage financial institutions to leverage digital technology to optimise service processes, reduce transaction costs, and improve the accessibility and convenience of financial services. Establish a robust

credit information sharing mechanism to eliminate information silos and provide more accurate financing services for SMEs.

3 Implement differentiated regulatory policies: Formulate differentiated regulatory policies according to the characteristics of enterprises of different scales, especially for large-scale enterprises, and make full use of their scale advantages in technology application to promote the optimisation of the debt maturity structure. Regulators can formulate different regulatory standards and requirements according to the scale, risk tolerance, and technology application level of enterprises. For large enterprises, we can encourage them to use advanced FinTech technology for risk management, optimise their debt structure, and reduce financing costs. For SMEs, we should focus on providing more financing channels and risk protection to help them overcome financing problems.

4 Standardise the application of blockchain technology: In view of the wide application of blockchain technology in supply chain finance and the possible 'technical arbitrage' problem, it is suggested to establish 'competition-neutral' rules for technology application to prevent algorithm discrimination and strengthen 'penetrating supervision' of blockchain platforms in supply chain finance, requiring core enterprises to share technical infrastructure. The government should issue relevant laws and regulations to clarify the application norms of blockchain technology in the financial field and ensure that all participants compete in a fair and transparent environment. At the same time, regulators should strengthen supervision of the blockchain platform, ensure its compliance operations, and prevent the use of technological advantages to conduct unfair competition or harm the interests of consumers.

5 Promote inter-departmental cooperation and information sharing: Encourage financial institutions, technology companies, regulatory agencies, and other parties to cooperate to jointly promote the development and application of FinTech, while strengthening information sharing and improving risk identification and prevention capabilities. The government should build a cooperation platform, promote exchanges and cooperation between different institutions, and jointly study and solve the problems encountered in the development of FinTech. Establish a sound information-sharing mechanism, promote data exchange among financial institutions, technology companies, and regulatory agencies, improve risk monitoring and early warning capabilities, and ensure the stable and healthy development of financial markets.

Competing interest

The authors declare no competing financial or non-financial interests.

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