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The Impact of Bank Fintech on Corporate Short-Term Debt for Long-Term Use—Based on the Perspective of Financial Risk

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Abstract: Information asymmetry between banks and enterprises in the credit market is essentially the microfoundation of financial risk generation. The frequent occurrence of corporate debt defaults, mainly due to the behavior of short-term debt for long-term use (hereinafter referred to as "SDLU"), further aggravates the contagion path from individual liquidity crisis to systemic repayment crisis. In order to test whether bank financial technology (hereinafter referred to as "BankFintech") can mitigate SDLU and reduce the possibility of financial risks, this study matched the loan data of China's A-share listed companies with the patent data of bank-invented Fintech from 2013 to 2022 to construct the BankFintech Development Index for empirical analysis. The empirical results show that the development of BankFintech can significantly inhibit SDLU. The mechanism test reveals that BankFintech reduces bank credit risk and liquidity risk by lowering firms' risk-weighted assets, improving capital adequacy and liquidity ratios, tilts banks' lending preferences toward duration-matched long-term financing, and "forces" enterprises to take the initiative to improve their financial health and information transparency, enhance their ability to obtain long-term loans, and realize the active management of mismatch risk. Heterogeneity analysis finds that the effect is more significant in non-state-owned enterprises and technology-intensive industries. Further analysis shows that the level of enterprise digitization, the intensity of financial regulation, and related financial policies significantly moderate the marginal effect between the two. This study verified the "Porter's Risk Mitigation Hypothesis" of Fintech, providing empirical evidence for effectively cracking the financial vulnerability caused by debt maturity mismatch and deepening financial supply-side reform.

Keywords: bank fintech; short-term debt for long-term use; information asymmetry; financial risk

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1. Introduction

In the wake of global economic digital transformation, financial risks arising from corporate debt maturity mismatches have become a common transnational challenge. Unlike developed markets such as the United States, which rely on a multi-tiered capital market to alleviate maturity mismatches, China and some emerging markets (e.g., India, Indonesia) exhibit significant financial repression characteristics, restricting long-term corporate financing channels, thereby exacerbating the phenomenon of "short-term debt used for long-term purposes". According to IMF data, by 2023, short-term debt in non-financial enterprises of emerging markets will account for 58%, far exceeding the 42% in developed countries. This structural imbalance is particularly acute in long-cycle industries such as territorial property and infrastructure.

Taking China Evergrande Group's 2021 debt crisis as an example, hindered sales collections forced the enterprise to utilize shadow banking nested structures to conceal its true liabilities, relying on "borrowing new to repay old" to maintain operations, resulting in a severe mismatch between short-term liabilities and real estate development cycle. This risk transmission mechanism exhibits three characteristics: Firstly, financial data distortion: Evergrande hid its debts through "off-balance sheet liabilities", making it difficult for conventional banks to identify them in time, relying on auditors' reports. Secondly, ambiguous capital flow: short-term debt funds were used for long-term real estate projects, with banks lacking cash flow penetration capabilities in post-lending management. Thirdly, delayed risk warning: rating agencies such as Moody's downgraded Evergrande's rating only three months before its default, exposing the pro-cyclical deficiencies of traditional risk control. Similar risk events spreading across regions in multinational companies like Brazil's Vale (2016 liquidity crisis) and South Korea's Lotte Group (2017 debt rollover default) reveal the systemic vulnerability formed from the interaction between financial accelerator effects (Bernanke et al., 1999) and regulatory arbitrage spaces (Kane, 1988) in emerging markets. This highlights the resonant risks of market discipline asymmetry and regulatory coordination lag during the embedding process of the global value chain.

Following 2013, the technological penetration rate in China's financial market experienced a significant surge, providing an innovative pathway to address the adverse selection risk arising from information asymmetry between banks and enterprises, as theorized by Akerlof (1970). Differentiating from the unidimensional credit assessment systems in European and American markets based on FICO scores, China's banking sector has constructed a penetrative risk control chain of "operational data $\rightarrow$ risk entropy value $\rightarrow$ capital allocation" through the analysis of unstructured data and dynamic risk pricing models (W. T. Ma et al., 2024), effectively mitigating term mismatch-induced systematic risks (Diamond, 1991). For instance, the "310" model of MyBank (3 min to file an application, 1 s to lend money, 0 manual intervention) evaluates the long-term repayment capability of small and micro-enterprises by leveraging e-commerce business transaction data, extending the average term of a loan from 6 to 14 months. To wit, by strengthening information constraints and dynamic pricing mechanisms, Fintech transforms the exogenous compliance costs of traditional regulation into endogenous incentives for enterprises to optimize their maturity structure, and provides a Chinese solution to the Akerlof-type information asymmetry dilemma of "lagged risk identification and distorted credit rationing".

Currently, a multidimensional research paradigm has been established regarding the impact of Fintech on credit allocation and enterprise development. Scholars generally confirm that Fintech can significantly enhance the credit accessibility of small and micro-enterprises by improving information-screening capabilities and optimizing soft information processing, among other methods (Zhang et al., 2022; Xu et al., 2021; Sheng & Fan, 2020). Furthermore, Fintech intensifies competition in the banking sector, thereby mitigating mismatches in investment and financing maturities (Y. He & Zhang, 2024). The Pecking Order Theory of Finance (Myers & Majluf, 1984) and the Credit Cycle Theory (Borio, 2014) also provide explanations for how Fintech, by alleviating information asymmetry, reconstructs the operational logic of the credit market and corporate financing behavior. The Credit Cycle Theory indicates that traditional banks, due to the "information island" effect, are prone to pro-cyclical credit expansion, whereas Fintech's real-time data monitoring can reduce the amplitude of credit cycle fluctuations (Li et al., 2022). From the perspective of the Pecking Order Theory, Fintech promotes a shift in corporate financing order from "internal funds $\rightarrow$ short-term debt $\rightarrow$ long-term debt" to "credit loans $\rightarrow$ long-term financing" by mitigating information asymmetry (Demirgüç-Kunt & Maksimovic, 1999; Frame & White, 2021). Similar transmission mechanisms are observed in developed markets (e.g., LendingClub's AI risk control model in the United States, open banking data sharing under the EU's PSD2 framework) and emerging economies (e.g., India's UPI system for real-time credit reporting, Brazil's digital bank Nubank using behavioral data modeling), demonstrating common characteristics that affirm Fintech as not merely a technological tool but also an institutional force reshaping credit decision-making logic.

It is worth noting that there exist two points of breakout in the existing literature: firstly, most of the current studies are based on correlation analysis, arguing that Fintech reduces SDLU by alleviating information asymmetry or optimizing soft information processing, but there is a lack of research on how Fintech affects the bank's own credit model and guides enterprise behavior to reduce SDLU; secondly, the research on the risks of SDLU mostly stays at the level of phenomenon description, and the transmission mechanism under the financial risk perspective has not yet been established. This text conducted an empirical study with China's Shanghai and Shenzhen A-share listed companies from 2013 to 2022 as the sample, and the possible contributions are as follows:

(1) Theoretical Framework Innovation: For the first time, a transmission framework is established that encompasses both the supply side of banking, characterized by "technological empowerment → dual enhancement of capital mobility and liquidity → expansion of long-term lending", and the demand side of enterprises, marked by "technological empowerment → hardening of financing conditions → proactive risk governance". This framework elucidates how BankFintech optimizes the capital structure of banks to achieve expansion in long-term lending, as well as how the "hardening" of financing conditions "action-forces" enterprises to proactively engage in risk governance to mitigate the impact of SDLU.
(2) Risk Governance Upgrade: Based on the framework of financial stability, it reveals that FinTech penetrates SDLU for risk identification and mitigation and provides tech-driven solutions for banks' digital transformation, corporate resilience enhancement, and prevention of systemic maturity structure mismatch risks.

2. Theoretical Analysis and Research Hypothesis Proposal

2.1. BankFintech and the Misuse of Short-Term Debt for Long-Term Purposes

The emergence of SDLU management among Chinese enterprises is a dual result of "active choice + passive constraint": there is either or both the cause of enterprises pursuing low-cost investment and financing, and the constraint on long-term credit supply from financial institutions and lack of non-determinant macro-policy. From the demand side, the cost of short-term financing is lower than that of long-term, which stimulates "borrowing short to invest long" interest arbitrage, verifying the "liquidity premium capture" theory (Diamond & Verrecchia, 1991). From the supply side, under conventional risk control models, banks lack effective tools for assessing the long-term project cash flows of enterprises, and the rise in the index of information asymmetry between banks and enterprises leads to an increase in the proportion of short-term loans, confirming Bharath and Shumway's (2008) "term insurance" hypothesis—banks reduce default exposure by shortening the term of a loan. This prudent strategy has led to a long-term, high proportion of short-term loans among non-financial enterprises in China, forming a rigid mismatch between investment and financing. The emergence of science and technology has alleviated this governance dilemma. Through "information chain reconstruction" and "risk chain interruption", banks' accuracy in identifying term mismatches ahead of time has improved, thereby promoting the extension of the term of a loan; post-loan, dynamic monitoring of ready money flow is achieved through technologies such as blockchain, which advances early warning of default and breaks the cycle of "short-term loan reliance—risk accumulation". In summary, the evolution of BankFintech know-how effectively suppresses enterprises' term arbitrage and gestion, and guides market entities to construct a cross-cycle Capital, Asset Quality, Management, Earnings, and Liquidity Rating System [CAMEL Rating System] allocation framework. For the reasons given above, we put forward a nuclear center hypothesis:

H1. *The development of BankFintech can inhibit the problem of enterprises using short-term debt for long-term purposes.*

2.2. Supply Side: BankFintech, Capital Liquidity, and Long-Term Financing Supply

Based on the liquidity transformation theory of financial intermediaries (Diamond & Dybvig, 1983), Fintech can monitor capital buffer levels in real time through the analysis of non-structured data, thereby reducing the cost of capital supplementation (Buchak et al., 2018) and enhancing the precision of credit risk assessment for applicants for a loan by banks (Berger & Udell, 2006). Banks adopting advanced risk models have a significantly lower proportion of risk-weighted assets to total assets compared to that of traditional banks (Altunbas et al., 2011), which leads to a reduction in the bank's liquidity mismatch index and compresses long-term credit premiums (Diamond & Dybvig, 1983). A typical case is the "Macro Risk Early Warning System" constructed by the People's Bank of China based on big data, which can identify mismatch risks in the territorial property industry six months ahead of time and increase short-term loan risk weights selectively. This action-forcing mechanism pushes banks to shift towards long-term credit. In other words, Fintech reconstructs the credit allocation efficiency of banks through dual pathways of "capital savings" and "liquidity management". This process drives a transition in credit supply structure from short-period arbitrage-driven interest to long-term value-oriented interest, providing a market solution to resolve systematic risks caused by term mismatch. For the reasons given above, we put forward the following hypothesis:

H2. *BankFintech reduces banks' risk-weighted assets while improving rate of capital sufficiency and reliability, optimizing capital utilization and long-term credit supply structure, lowering credit risk and reliability risk, forming a transmission mechanism from "science and technology empowerment $\rightarrow$ dual rise in capital reliability $\rightarrow$ expansion in long-term loans".*

2.3. Demand Side: BankFintech, Information Screening, and Proactive Risk Governance

On the basis of Akerlof's (1970) "Lemon Market" theory, traditional credit markets face adverse selection due to information asymmetry between banks and enterprises, leading to the squeezing out of high-quality enterprises (Stiglitz & Weiss, 1981). The development of BankFintech alleviates the limitations of banks' information-screening capabilities, while at the same time forcing enterprises to proactively enhance their financial health conditions and the quality of information disclosure. Firstly, banks employ machine learning algorithms to construct enterprise credit scoring models, hooking onto financial health to finance costs directly, shifting from a "scale preference" to a "quality preference", imposing "hard constraints" that incentivize enterprises to proactively carry out risk avoidance. Enterprises, in turn, differentiate themselves from low-quality ones by disclosing high-quality financial information to the market, thereby diffusing signs, sounds, and images of low risk. Secondly, the "intelligent risk control hard constraints" of BankFintech forces enterprises to have a need to disclose operating information truthfully, action-forcing enterprises to undergo a demand-side behavior transformation of "seeking financing first requires transparency". To obtain long-term loans from financial technology banks, enterprises proactively enhance their information transparency clarity index. This path pushes firms to shift from passive regulatory compliance to endogenous financial optimization, reshaping the risk-return equilibrium in the credit market and providing a theoretical anchor for sovling the debt maturity mismatch dilemma in emerging markets.

H3. *BankFintech action-forcing enterprises to proactively improve financial health and information transparency clarity through enhanced information-screening capabilities, thereby boosting their capacity to obtain long-term loans and forming a transmission mechanism of "technological empowerment-financing conditions hardening-proactive risk governance".*

Based on the above analysis, the theoretical analysis framework of this paper is shown in Figure 1 below:

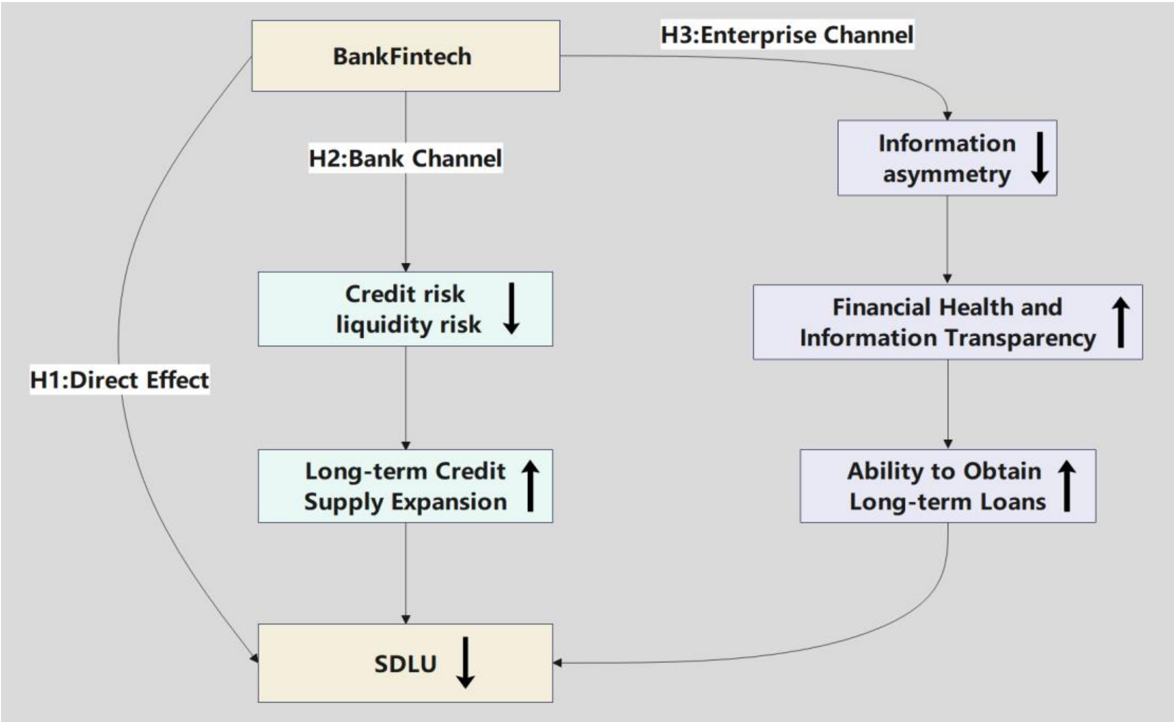

Figure 1. Theoretical mechanism.

3. Research Design

3.1. Sample Selection and Data Sources

This text takes the listed companies on the Shanghai and Shenzhen main boards from 2013 to 2022 as research subjects. The data at the company, industry, and macro bedding plane levels are primarily sourced from the CSMAR database. The BankFintech Indicator is mainly measured through Fintech patents invented by banks, and weights are set with the help of detailed loan bank data disclosed by the CSMAR database, forming a company-level BankFintech Indicator. Patent data are sourced from the announcements of patent publications by the China National Intellectual Property Administration.

The following treatments were carried out on the data: (1) Excluding ST, ST*, and PT companies; (2) excluding financial companies; (3) a two-sided trimming treatment of 1% on continuous variables involved in this text so as to avoid the influence of extreme values of continuous variables. Additionally, in order to ensure the accuracy of empirical results, samples with energy in terms of the amount of loans and non-causal loan banks were excluded. Ultimately, there are a total of 11,960 sample observations, involving 1196 companies among which state-owned companies account for 470 while banks account for 205.

3.2. Variable Measurement

3.2.1. Explained Variable: Short-Term Debt for Long-Term Use by Enterprises (SDLU)

In alignment with the research methodology employed by X. G. Liu and Liu (2019), this text employs the difference between the proportion of short-term liabilities and the proportion of short-term assets within a firm to assess the extent of its practice of utilizing short-term debt for long-term purposes. The proportion of short-term liabilities is defined as the ratio of a firm's short-term liabilities to its total liabilities, whereas the proportion of short-term assets is the ratio of a firm's short-term assets to its total assets. The calculation formula is as follows:

$$SDLU_{i,t} = \frac{STL}{TL} - \frac{STA}{TA} \tag{1}$$

Here, STL represents short-term liabilities, which consist of temporary loans, accounts payable, accrued interest payable, notes payable, emoluments payable to staff, taxes payable, dividends payable, administration fees and middleman's fees payable, and non-current liabilities that are maturing within one year. TL stands for total liabilities. STA represents short-term assets, including monetary fund, net temporary investment, net accounts receivable, net bill receivable, net dividend receivable, net accrued interest receivable, net other receivables, net stock-in-trade, and non-current assets that are maturing within one year. TA signifies total assets. A higher value of this indicator clearly states that the proportion of short-term liabilities exceeds that of short-term assets, indicating a deeper level of utilizing short-term debt for long-term purposes.

3.2.2. Core Explanatory Variable: Bank Financial Technology (BankFintech)

In accordance with the study by Li et al. (2022), this text carries out manual dressing by rescreening of individual loan records of enterprises as documented in the CSMAR database, and calculates the bank financial technology indicator through weighting in combination with the number of bank patents and the scale of vocational work. The specific definition is as follows:

$$BankFintech_{i,t} = \sum\nolimits_{n=1}^{N} \frac{patent_{i,n,t}}{\Sigma patent_{i}} \times \frac{b\_size_{i,n,t}}{\Sigma b\_size_{i,t}} \tag{2}$$

Among the rest, $\frac{patent_{i,n,t}}{\Sigma patent_{i}}$ represents the proportion of financial technology patents invented by a loan bank of a certain enterprise in a given year to the total number of financial technology patents invented by all sample banks in that year; $\frac{b\_size_{i,n,t}}{\Sigma b\_size_{i,t}}$, to wit, is the weighting calculation based on the bank's assets. A larger value of Bankfintech indicates a more significant impact of bank financial technology on the enterprise.

3.2.3. Mechanism Variables

Total Risk-Weighted Assets (TRWA): The sum of credit risk-weighted assets, market risk-weighted assets, and operational risk-weighted assets.

Capital Adequacy Ratio (CAR): The proportion of compliant regulatory capital to total risk-weighted assets.

Liquidity Ratio (Liquidity Ratio): The ratio of liquid assets to liquid liabilities.

Corporate Financial Health (Z-score): A comprehensive risk index constructed by integrating multiple dimensions such as liquidity, earning power, repayment capability, and operational efficiency.

Quality of Corporate Information Disclosure (KV): Referencing the study by Kim and Verrecchia (2001), a model is constructed based on the closing price and trading volume of corporate stocks, and the impact coefficient of trading volume on returns is calculated, known as the KV index. A lower KV index indicates higher quality of information disclosure by quoted companies.

3.2.4. Control Variables

Referring to currently available studies, this text divides the selection of control variables into three bedding planes: enterprise, industry, and macro. The control variables at the enterprise bedding plane consist of fixed asset ratio (Fix), leverage ratio (Lev), cash flow status (Cash), and multiple interest coverage (ICR); the control variables at the industry bedding plane consist of industry competition degree (Industry-HHI) and number of financial institution in the banking sector (BFI); the control variables at the macro bedding plane consist of monetary policy environment (M2) and economic development level of each province (GDP). These variables, in posse, are able to have an impact on SDLU. The specific definitions of these variables are shown in Table 1 below.

Table 1. Symbols and definitions of major variables.

Variable Symbol	**Variable Definition**
Explained Variable	
SDLU	Enterprise short-term debt and long-term use: the difference between the proportion of short-term liabilities and the proportion of short-term assets.
Core Explanatory Variable	
BankFintech	Calculated based on the Fintech patents invented by the bank and the size of the corresponding lending bank of the enterprise.
Mechanism Variables	
TRWA	Bank risk-weighted assets: sum of credit risk-weighted assets, market risk-weighted assets, and operational risk-weighted assets
CAR	Bank Capital Adequacy Ratio: Compliance Regulatory Capital/Risk-Weighted Assets × 100%
LiquidityRatio	Bank Liquidity Ratio: Liquid Assets/Liquid Liabilities × 100%
Z-Score	Corporate financial health: Z-Score score
KV	Corporate disclosure quality: coefficient of impact of trading volume on rate of return
Control Variables	
Fix	Fixed Asset Ratio: Net Fixed Assets/Total Assets
Lev	Financial Leverage Ratio: Total Liabilities/Total Assets
Cash	Cash Flow Position: Net Cash Flow from Operating Activities/Total Assets at the Beginning of the Period
ICR	Interest Coverage Multiple: EBITDA/Interest Expense
Industry-HHI	Industry Competitiveness: Herfindahl–Hirschman Index
BFI	Number of financial institutions in the banking sector
m2	Monetary policy environment: broad money growth rate
GDP	Level of economic development: GDP growth rate of each province

3.3. Model Construction

3.3.1. Two-Way Fixed Effects Model

This paper constructs a two-way fixed effects model to verify Hypothesis 1:

$$\mathrm{SDLU}_{i,t} = \beta_0 + \beta_1 \times \mathrm{BankFintech}_{i,t} + \gamma \times \mathrm{controls}_{i,t} + \eta_i + \lambda_i + \varepsilon_{i,t} \quad (3)$$

In this context, the dependent variable "SDLU" (short-term debt for long-term use) represents the level of firms' maturity mismatch, with the core explanatory variable "BankFintech" measuring banks' Fintech intensity. The model incorporates control variables (controls) that may impact firms' SDLU. Given that many Fintech patents might not be put into use in the year of application, the dependent variable is lagged by one period in the regression specification to account for technological implementation delays. η_i and λ_i indicates enterprise-fixed effects and year-fixed effects, respectively, while $\varepsilon_{i,t}$ serves as the random disturbance term.

3.3.2. Mediating Effect Model

This text employs the mediation two-step method to test Hypotheses 2 and 3. The main idea is to explore the mechanism through which the independent variable influences the dependent variable in empirical regression analysis. This can be achieved by analyzing the relationship between the independent variable and the mediating variable to reveal its impact path, and by combining existing theories or the literature viewpoints to elaborate on the relationship between the mediating variable and the dependent variable. Therefore, this text sets up the following models for the independent variable and the mediating variable:

$$\text{BankMechanism}_{i,t} = \beta_0 + \beta_1 \times \text{lnBank\_Patent}_{i,t} + \gamma \times \text{control}_{i,t} + \eta_i + \lambda_i + \varepsilon_{i,t} \quad (4)$$

$$\text{EnterpriseMechanism}_{i,t} = \alpha_0 + \alpha_1 \times \text{BankFintech}_{i,t} + \gamma \times \text{control}_{i,t} + \eta_i + \lambda_i + \varepsilon_{i,t} \quad (5)$$

In Equation (4), which is used to test Hypothesis 2, where "lnBank_Patent" represents the logarithm of the number of fintech patents invented by banks, "BankMechanism" includes Capital Adequacy Ratio (CAR) and Liquidity Ratio; Equation (5) is used to test Hypothesis 3 with "EnterpriseMechanism" representing Z-Score and KV Index. Definitions of Controls, firm fixed effects, time fixed effects, and error term are consistent with Model (1).

3.4. Statistical Analysis of Key Variables

Figure 2 illustrates the number of financial technology patents developed by state-owned large commercial banks, stock-holding commercial banks, urban commercial banks, and rural commercial banks (limited to representative samples) in China from 2013 to 2022. This figure conveys the following insights:

(1) Overall Trend: From 2013 to 2017, the number of financial technology patents in China's commercial banks remained at a low level. However, a rapid growth trend emerged post-2018, culminating in a total of 4025 patents by 2022. This reflects a significant improvement in the banking sector's innovation investment in the financial technology domain over time.

(2) Variance by Bank Type: State-owned large commercial banks experienced an explosive growth in patent numbers post-2020, reaching 3589 patents by 2022. These banks have become the core driving force behind the overall growth in financial technology patents, highlighting their resource advantages and dominant position in financial technology research and development. Stock-holding commercial banks saw a noticeable rise in patent numbers post-2019, peaking at 549 patents in 2021 but falling back to 407 patents in 2022, indicating some fluctuations in their innovation investment. Urban and rural commercial banks have long maintained a low level of patented inventions, particularly rural commercial banks, whose annual patent counts significantly lag behind those of other bank types. This underscores resource constraints and capacity disparities in their financial technology research and development efforts.

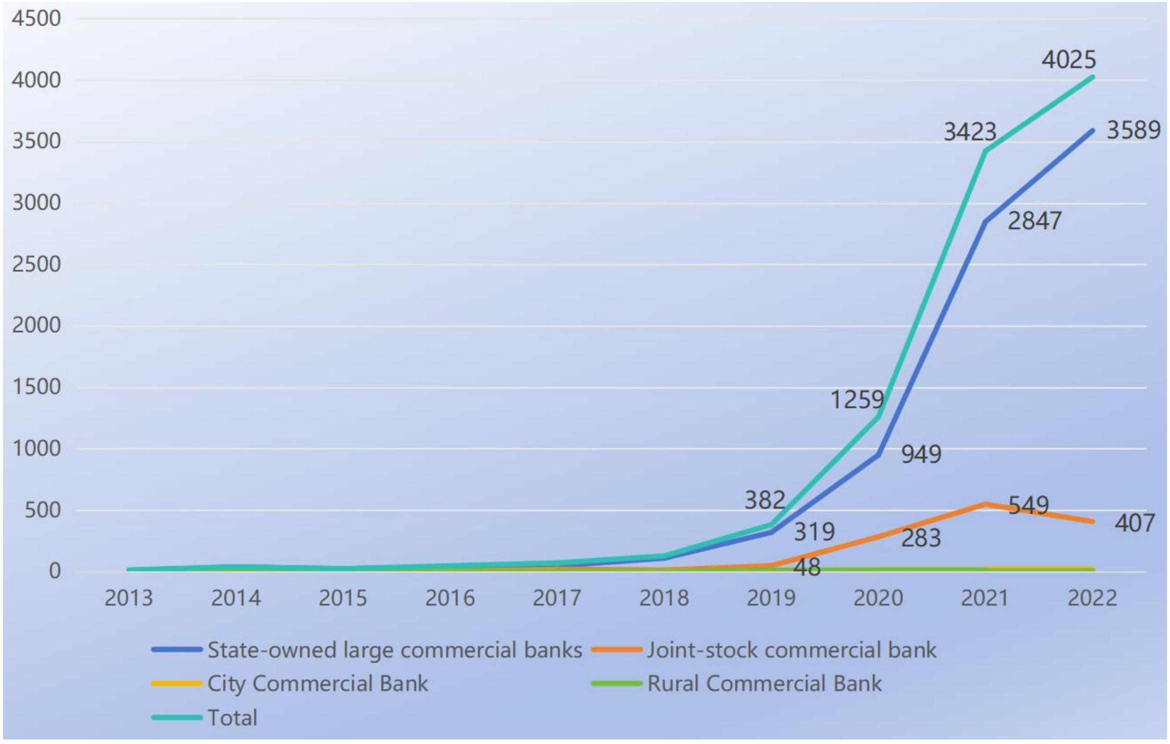

Figure 2. The number of Fintech patent inventions of different types of banks.

In summary, the financial technology patent inventions by China's commercial banks exhibit characteristics of "state-owned large banks leading the charge, overall high-speed growth, but with imbalances in development among different bank types".

The two broken lines in Figure 3 represent the trends of the total number of financial technology patents issued by sample banks in China from 2013 to 2022 and the non-performing loans, respectively. The following information can be analyzed from the trend in the figure:

(1) 2013–2017: The number of financial technology patents was at an extremely low level, while the non-performing loan ratio continued to rise (from 0.0084 to 0.0153), which reflected that during this period, the application of financial technology in banks was insufficient and risk management relied more on conventional models, making it difficult to effectively curb the rising trend of non-performing loan ratios.

(2) 2018–2020: The number of financial technology patents began to grow gradually, and the non-performing loan ratio showed a moderating trend (from 0.0135 down to 0.0123), indicating that the application of financial technology patents might have enhanced the banks' ability to identify and manage risks, with technological means playing a positive role in reducing non-performing loan ratios.

(3) 2021–2022: The number of financial technology patents experienced explosive growth (reaching a peak value in 2022), but the non-performing loan ratio slightly increased (from 0.01212 to 0.0134). This phase requires a comprehensive consideration of complex factors such as the external economic environment. Although increased investment in financial technology, if macroeconomic fluctuations and other shocks exceed the effects of technological optimization, it may still lead to short-term fluctuations in non-performing loan ratios. However, in the long run, it still demonstrates the potential supportive role of accumulated financial technology patents in bank risk control.

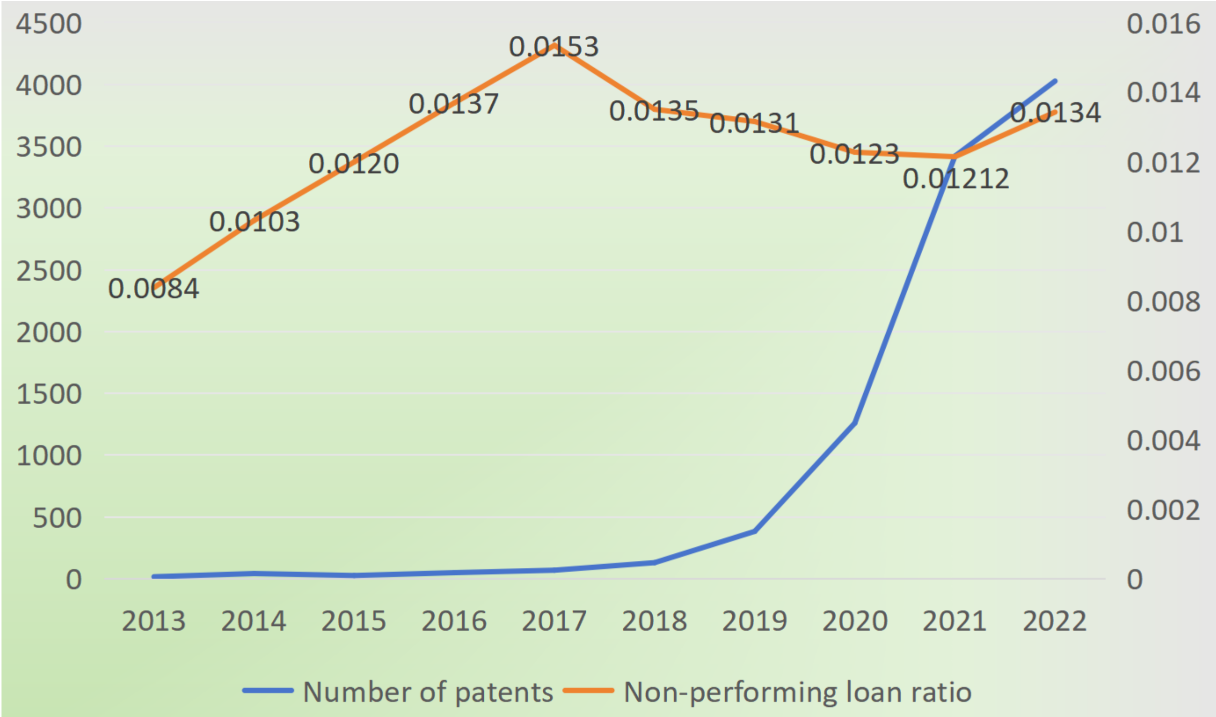

Figure 3. The trends of the number of Fintech patents in sample banks and the non-performing loan ratio.

Overall, the growth in the number of financial technology patents is correlated with the trend of non-performing loan ratios in a phased manner, reflecting that increased technological investment to a certain degree helps optimize credit quality and curb irrational rises in non-performing loan ratios.

4. Empirical Results

4.1. Benchmark Regression Result

Table 2 presents the regression results of BankFintech on the dual fixed effects of short-term debt used for long-term purposes (SDLU) at the enterprise level. Column (1) includes only control variables at the enterprise level, while Column (2) incorporates control variables at the enterprise, industry, and macro levels. The results indicate that BankFintech can significantly reduce SDLU, thereby supporting Hypothesis 1 in this text. The control variables reveal that an increase in the corporate leverage ratio (Lev) creates an exposure to risk, leading to a sharp rise in debt repayment pressures. The cash flow level (Cash) and interest coverage ratio (ICR) represent the liquidity risk (ability to repay principal on time) and profitability coverage risk (ability to pay interest on time) of the enterprise, respectively, both of which are significantly negatively correlated with SDLU. This implies that an improvement in repayment capability can effectively alleviate SDLU. An increase in the number of banking financial institutions (BFI) is significantly positively correlated with SDLU. This text posits that while an increase in the number of banking institutions may alleviate financing constraints in aggregate, it could potentially exacerbate short-term debt used for long-term purposes in some enterprises through regulatory arbitrage. Therefore, it is necessary to guide the matching of funding tenors with enterprise assets through institutional design to prevent the accumulation of systematic risk.

Table 2. Benchmark regression analysis.

	(1)	(2)
	SDLU	SDLU
BankFintech	−0.464 **	−0.479 **
	(0.206)	(0.212)
Fix	−0.433	−0.417
	(0.545)	(0.556)
Lev	0.128 *	0.126 *
	(0.074)	(0.075)
Cash	−0.087 **	−0.087 **
	(0.038)	(0.039)
ICR	−0.116 ***	−0.116 ***
	(0.040)	(0.041)
Industry-HHI		−0.162
		(0.577)
BFI		1.404 *
		(0.799)
M2		−0.185
		(1.503)
GDP		1.198
		(1.989)
_cons	−0.790 **	−19.483 **
	(1.021)	(9.515)
Id/Year FE	YES	YES
Observations	3378	3315

Note: *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively. The robust standard errors are shown in parentheses. The same applies to the following tables.

4.2. Robustness Tests

4.2.1. Substitution of Core Explanatory Variables

In reference to the study by Xie and Wang (2022), this paper replaces BankFintech with the level of bank digitization (Bank Digitization) for robustness testing. The data are sourced from the Digital Finance Research Center of Peking University. The indicator system is constructed from three dimensions: strategic digitization, operational digitization, and management digitization of commercial banks. Principal component analysis is employed to construct the weights of the indicators, providing a comprehensive and objective assessment of the digital transformation and development trends of China's commercial banks. As shown in Table 3, as well as columns (1) and (2), a higher Bank Digitization corresponds to a lower SDLU, confirming the robustness of the basic regression results.

Table 3. Replacement of Core Explanatory Variables and Explained Variables.

	(1)	(2)	(3)	(4)
	Replacement of Core Explanatory Variables		Replacement of Explained Variables	
	SDLU	SDLU	SFLI	SFLI
Bank Digitization	−0.004 *	−0.004 *		
	(0.002)	(0.002)		
BankFintech			−0.038 *	−0.038 *
			(0.022)	(0.022)
Fix	−0.051	−0.057	−0.074	−0.076
	(0.487)	(0.496)	(0.058)	(0.058)
Lev	−0.141 **	−0.153 **	−0.012	−0.014 *
	(0.062)	(0.066)	(0.008)	(0.008)

Table 3. *Cont.*

	(1)	(2)	(3)	(4)
	Replacement of Core Explanatory Variables		Replacement of Explained Variables	
	SDLU	**SDLU**	**SFLI**	**SFLI**
Cash	-4.719×10^8	-3.834×10^8	−0.010 **	−0.011 ***
	(1.508×10^9)	(1.557×10^9)	(0.004)	(0.004)
ICR	−0.102 ***	−0.107 ***	0.006	0.007 *
	(0.033)	(0.034)	(0.004)	(0.004)
Industry-HHI		0.005		−0.169 ***
		(0.490)		(0.060)
BFI		3.239 **		−0.031
		(1.283)		(0.084)
M2		1.454		0.097
		(1.323)		(0.158)
GDP		2.322		−0.198
		(1.861)		(0.209)
_cons	1.522 ***	−64.090 ***	−0.309 ***	0.660
	(0.249)	(22.941)	(0.107)	(0.998)
Id/Year	YES	YES	YES	YES
Observations	3701	3629	3244	3206

Note: *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively. The robust standard errors are shown in parentheses. The same applies to the following tables.

4.2.2. Substitution of Explained Variables

Drawing from the research by M. Yang and Wu (2022), SDLU is replaced with the degree of mismatch between investment and financing tenors (SFLI) for robustness testing. The calculation formula for SFLI is: SFLI = frac{[text{Cash outflows for investing activities (e.g., purchase and construction of fixed assets)} − text{Increase in long-term borrowings in the current period} + text{Increase in equity in the current period} + text{Net cash flow from operating activities} + text{Cash inflows from fixed asset sales}]}/text{Total assets of the previous year}. After re-running the regression, it is found that the research conclusions remain unchanged. The results are presented in Table 3, as well as columns (3) and (4).

4.2.3. Instrumental Variable Approach

In the interest of addressing endogeneity issues more effectively, this text employs provincial-level scientific and technological innovation investment (Tech-Innovation) as an instrumental variable for BankFintech. This instrumental variable meets two critical conditions: (1) Relevance: Provincial scientific and technological innovation investment maintains a direct correlation with the development of bank financial technology. Government support for science and technology (e.g., R&D subsidies, talent policies) elevates regional digital infrastructure levels, thereby propelling the digital transformation of banking technologies. (2) Exogeneity: Provincial scientific and technological investment is primarily driven by government strategic planning, remaining independent of the micro-level policy-making of individual banks or enterprises. The data are sourced from The National Statistical Bulletin on Investment in Science and Technology Funds (annual), jointly published by the National Bureau of Statistics, the Ministry of Science and Technology, and the Treasury Department.

Table 4 gives an account of the check result for the instrumental variable. The weak IV test indicates that the mean Cragg–Donald Wald F statistic is 19.927, exceeding the 10% critical value of 16.38 from Stock–Yogo, thus passing the weak IV test. The Anderson canonical correlation LM statistic for the identification test rejects the null hypothesis at the 1% level, satisfying the identifiability of the instrumental variable. After taking into account endogeneity issues, the impact of BankFintech on SDLU remains significantly negative, underscoring the robustness of the regression results.

Table 4. Instrumental variable approach.

	(1) First	(2) Second
	BankFintech	**SDLU**
Tech-Innovation	0.0132 ***	
	(4.46)	
BankFintech		−10.3581 **
		(−1.97)
Fix	−0.0315	0.1755
	(−1.44)	(0.32)
Lev	0.0041 *	0.3880 ***
	(1.76)	(6.55)
Cash	0.0007	−0.6289 ***
	(0.29)	(−11.10)
ICR	0.0047	−0.0800
	(1.62)	(−1.10)
Industry-HHI	−0.0285	0.8251
	(−1.39)	(1.62)
BFI	0.2697 ***	−2.6581 *
	(10.02)	(−1.71)
M2	0.6564 ***	−9.9571 **
	(5.56)	(−2.21)
GDP	−0.6235 ***	10.3849 **
	(−4.26)	(2.17)
_cons	−4.1287 ***	27.3396
	(−9.43)	(1.14)
Cragg–Donald Wald F statistic (critical value)	19.927 (16.38)	
Anderson canonical correlation LM statistic (*p* value)	19.868 *** (0.000)	
Observations	3313	3313

Note: *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively. The robust standard errors are shown in parentheses. The same applies to the following tables.

4.2.4. PSM Approximate Sample Matching

This text addresses the issue of sample selection bias through the agency of the PSM method. Using the firm's financing constraint SA as an indicator for grouping, the research sample is divided into a group with high financing constraints and a group with hypothesized low financing constraints. In Table 5, Psmatch2 results indicate that the correlation coefficient between BankFintech and SDLU is −0.528, and the t-value of the ATT treatment effect is 3.43, which exceeds the critical value of 2.56 at the 1% level, thereby alleviating endogeneity issues caused by sample selection bias. In Table 6, Bootstrap results show that all three estimation outcomes pass the test of significance, giving an account of the statistical reliability of BankFintech's impact on SDLU and further validating the robustness of the estimation results.

Table 5. Psmatch2 results.

Variable	Sample	Treated	Controls	Difference	S.E.	T-Stat
SDLU	Unmatched	1.0384872	1.19423777	−0.155750572	0.119632839	1.3
	ATT	1.03933692	1.56690546	−0.527568534	0.153869509	3.43
	ATU	1.19423777	0.857559298	−0.33667847		
	ATE			−0.430403772		

Table 6. Bootstrap results.

	Observed Coefficient	Bootstrap Std. Err.	z	P > z	Normal-Based [95% Conf. Interval]	
_bs_1	0.528	0.18	2.94	0.003	0.176	0.879
_bs_2	0.337	0.136	2.48	0.013	0.071	0.602
_bs_3	0.43	0.138	3.11	0.002	0.159	0.702

Figure 4 illustrates the cross reference of standardized deviations of covariates before and after Propensity Score Matching (PSM). Following PSM, the standardized deviations of most covariates were significantly reduced, indicating that the matching process successfully precluded the initial Variance between the hypo-financing constraint group and the high-financing constraint group, thereby enhancing the comparability of the advanced compilation. This validates the effectiveness of PSM in controlling selection bias.

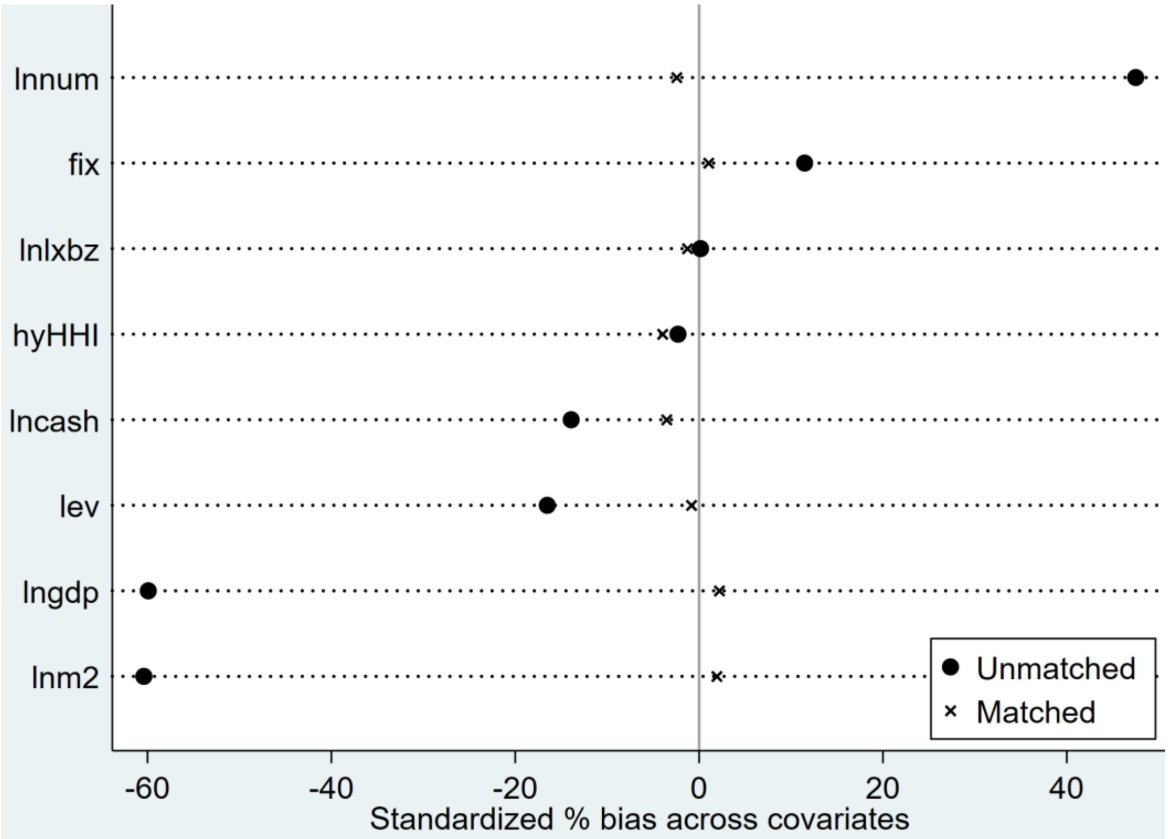

Figure 4. Comparison of standardized mean differences in covariates.

In Figure 5, the significant overlap between red (treatment group) and blue (control group) within the propensity score range of 0.2–0.8 demonstrates that the common support region is plentiful, ensuring the effectiveness of the matching. The green moiety accounts for an extremely low proportion, indicating that few treatment group samples were excluded. PSM, while preserving the samples, controlled selection bias through common support, validating the optimization effect of the matching process on inter-group comparability.

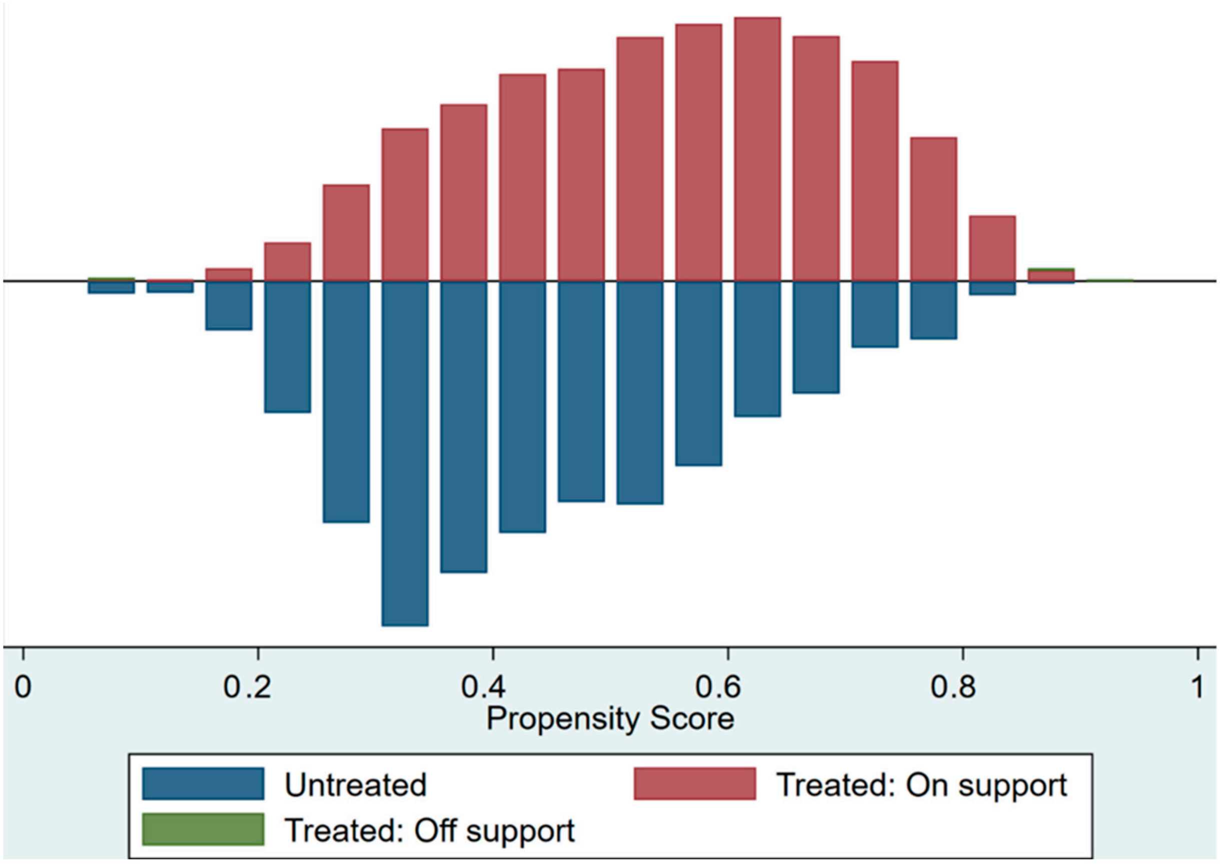

Figure 5. Common support domain of propensity scores.

4.3. Analysis of Heterogeneity

4.3.1. Analysis of Heterogeneity Based on Enterprise Property Rights

This study categorizes the sample into State-Owned Enterprises (SOEs) and Non-State-Owned Enterprises (Non-SOEs) for comparative analysis, with the empirical results summarized in Table 7. The impact of BankFintech on the level of short-term debt used for long-term purposes is insignificant for SOEs ($\beta = -0.341$, $p > 0.1$), while it is significantly influential at the 5% level for Non-SOEs ($\beta = -0.674$ **, $p < 0.05$). Based on the theory of soft budget constraints (Kornai, 1986) and the theory of credit rationing (Stiglitz & Weiss, 1981), the institutional differences between SOEs and Non-SOEs define the operational boundaries of financial technology. SOEs typically maintain long-term, stable cooperative relationships with financial institutions such as banks, granting them certain advantages in accessing credit resources and facilitating easier acquisition of long-term credit. Consequently, their motivation for using short-term debt for long-term purposes is relatively weak, diluting the discriminatory value of financial technology. In contrast, Non-SOEs face ownership discrimination and profit pressures, often utilizing short-term debt for long-term purposes as a form of liquidity arbitrage. Financial technology, through data penetration and blockchain-based fund supervision, emerges as a pivotal tool in addressing the “short-term loan dependency–maturity mismatch” issue. This divergence stems from the fundamental distinction between “government credit substitution” in SOEs and “technical risk pricing” in Non-SOEs.

Table 7. Heterogeneity analysis by enterprise ownership nature.

	(1) SOEs	(2) Non-SOEs
	SDLU	SDLU
BankFintech	−0.341	−0.674 **
	(−0.990)	(−2.439)
Fix	0.108	−0.929
	(0.114)	(−1.301)
Lev	0.091	0.160 *
	(0.684)	(1.743)
Cash	−0.032	−0.130 ***
	(−0.461)	(−2.670)
ICR	−0.138 *	−0.102 **
	(−1.950)	(−1.988)
Industry-HHI	−0.589	0.516
	(−0.634)	(0.640)
BFI	0.853	2.039 **
	(0.619)	(2.043)
M2	1.396	−1.134
	(0.528)	(−0.619)
GDP	−1.000	2.718
	(−0.285)	(1.127)
_cons	−13.041	−27.676 **
	(−0.805)	(−2.307)
Id/Year FE	YES	YES
Observations	1422	1893

Note: *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively. The robust standard errors are shown in parentheses. The same applies to the following tables.

4.3.2. Heterogeneity Analysis of Industries

This text further makes a study of enterprises by splitting them up into labor-intensive, capital-intensive, and technology-intensive industries based on the structure of factor of production inputs. The empirical results are shown in Table 8 below. Among the rest, in technology-intensive industries, the negative impact of BankFintech on enterprises' short-term debt long use is significant at the 5% level ($\beta = -0.755$ **, $p < 0.05$). For labor-intensive industries, it is negatively significant at the 10% level ($\beta = -0.678$ *, $p < 0.1$). In capital-intensive industries, there is no impact ($\beta = 0.041$, $p > 0.1$). This text was of the opinion that for technology-intensive enterprises, their degree of digitalization is relatively high; thus, the BankFintech model can more easily and accurately penetrate to form strong constraints to inhibit SDLU. Labor-intensive industries mostly involve non-structured data; hence, there are error rates in fintech recognition which affect intervention precision. Capital-intensive industries place reliance upon hypothecation financing; conventional risk control has already covered duration mismatch risks, leading to the marginal ineffectiveness of technological measures.

Table 8. Industry heterogeneity analysis.

	(1) Labor-Intensive	(2) Capital-Intensive	(3) Technology-Intensive
	SDLU	SDLU	SDLU
BankFintech	−0.678 *	0.041	−0.755 **
	(−1.653)	(0.125)	(−1.983)
Fix	−0.792	0.364	−1.543
	(−0.793)	(0.415)	(−1.248)
Lev	0.093	0.063	0.459 **

Table 8. *Cont.*

	(1) Labor-Intensive	(2) Capital-Intensive	(3) Technology-Intensive
	SDLU	**SDLU**	**SDLU**
	(0.744)	(0.517)	(2.401)
Cash	−0.052	−0.092	−0.132 **
	(−0.598)	(−1.508)	(−2.026)
ICR	−0.080	−0.142 **	−0.158 **
	(−1.007)	(−2.103)	(−2.152)
Industry-HHI	−0.049	0.286	−0.651
	(−0.047)	(0.336)	(−0.545)
BFI	2.078	0.565	1.955
	(1.341)	(0.453)	(1.396)
M2	−1.187	0.007	0.381
	(−0.390)	(0.003)	(0.154)
GDP	2.496	0.162	1.557
	(0.627)	(0.052)	(0.469)
_cons	−22.277	−6.389	−35.475 **
	(−1.214)	(−0.426)	(−2.124)
Id/Year FE	YES	YES	YES
Observations	1057	1089	1169

Note: * and ** represent the significance levels of 10% and 5%, respectively. The robust standard errors are shown in parentheses. The same applies to the following tables.

5. Further Analysis

5.1. Mechanism Testing

5.1.1. BankFintech, Capital Liquidity, and Long-Term Financing Supply

To verify Hypothesis 2, this text collected empirical data on the cumulative number of financial technology patents and relevant financial indicators for 205 banks from 2013 to 2022. The adoption of BankFintech is represented by the natural logarithm of the cumulative number of financial technology patents invented by banks in the current year (lnBankPatent). Control variables include the bank's own scale (Size), age (Age), earning power (ROA), assets–liabilities ratio (DAR), and total asset turnover (AT), as well as macro-level indicators such as the number of banking financial institutions (BFIs) and the Gross Domestic Product of the financial industry by province (Financial_GDP).

Table 9 presents the impact of BankFintech on bank credit risk. Regression results indicate that BankFintech significantly reduces banks' Total Risk-Weighted Assets (TRWA) and enhances their Capital Adequacy Ratio (CAR). Table 10 further shows a significant positive correlation between BankFintech and bank liquidity (Liquidity Ratio), thereby reducing liquidity risk. These findings emit crucial signals. From the perspective of long-term financing supply, a decrease in TRWA directly reflects a reduction in banks' reliance on high-risk borrowers (e.g., decreased lending to enterprises with low credit ratings), leading to a lower probability of default and loss given default. Research reports from the BIS in 2022 indicate that a 10% reduction in TRWA corresponds to an average decrease of 0.5 percentage points in the non-performing loan ratio (NPL). A higher CAR signifies a more robust capital base, enabling banks to absorb potential losses more effectively. Banks with higher CAR can utilize capital buffers to absorb losses in the event of loan defaults, thereby avoiding forced asset sell-offs or credit contraction. An increase in Liquidity Ratio ensures short-term repayment capacity and long-term fund stability by directly covering short-term liabilities with high-quality liquid assets, reducing the risk of a run on a bank. The synergistic effect of these two factors allows for more robust long-term financing provisions to the real economy, mitigating credit squeezes caused by internal risk fluctuations.

Table 9. BankFintech and credit risk.

	(1)	(2)	(3)	(4)
	Credit Risk			
	Total Risk Weighted Assets		Capital Adequacy Ratio	
lnBank_Patent	−0.044 ***	−0.049 ***	0.439 ***	0.364 ***
	(0.010)	(0.012)	(0.077)	(0.085)
Size		0.089 ***		0.506 ***
		(0.016)		(0.099)
Age		0.030		−0.087
		(0.018)		(0.126)
ROA		7.828 **		63.715 ***
		(3.217)		(20.419)
DAR		−2.482 ***		−14.563 ***
		(0.432)		(2.740)
AT		−2.890 **		2.587
		(1.273)		(8.269)
BFI		0.303 *		−1.640
		(0.167)		(1.122)
Financial_GDP		0.071		0.149
		(0.061)		(0.370)
_cons	25.182 ***	21.571 ***	13.118 ***	27.712 ***
	(0.015)	(1.581)	(0.102)	(10.527)
Id/Year FE	YES	YES	YES	YES
Observations	1504	1294	1659	1421

Note: *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively. The robust standard errors are shown in parentheses. The same applies to the following tables.

Table 10. BankFintech and liquidity risk.

	(1)	(2)
	Liquidity Risk–Liquidity Ratio	
lnBank_Patent	2.342 ***	2.977 ***
	(0.516)	(0.605)
Size		−2.451 ***
		(0.754)
Age		0.638
		(0.909)
ROA		−327.021 **
		(151.065)
DAR		63.253 ***
		(20.753)
AT		104.947 *
		(61.659)
BFI		−18.690 **
		(8.263)
Financial_GDP		2.946
		(2.786)
_cons	10.551 ***	154.028 **
	(0.706)	(77.523)
Id/Year FE	YES	YES
Observations	1493	1287

Note: *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively. The robust standard errors are shown in parentheses. The same applies to the following tables.

5.1.2. BankFintech, Information Screening, and Proactive Risk Governance

On the basis of Table 11, it is evident that BankFintech exhibits a significant positive correlation with corporate financial health (Z-Score) and a significant negative correlation with information disclosure quality (KV), where a lower KV Index indicates higher information disclosure quality. Hypothesis 3 has thus been validated. BankFintech facilitates a shift from "passive financing" to "active planning" among enterprises, prompting proactive optimization of the Z-Score and a transformation from "window dressing financial statements" to "authentic business operations", thereby enhancing KV. This process not only curbs the interest arbitrage motives of SDLU but also remolds the underlying logic of risk pricing and regulatory intervention, effecting a paradigm shift in financial resource allocation from a "collateral-dependent extensive trust mechanism" to a "data-driven refined risk control system". Future efforts should focus on bridging data silos and deepening the application of algorithms in risk early warning to achieve a dynamic equilibrium between financial stability and scientific and technological innovation.

Table 11. The impact of BankFintech on corporate financial health and information disclosure quality.

	(1)	(2)	(3)	(4)
	Corporate Financial Health		Information Disclosure Quality	
	Z-Score	Z-Score	KV	KV
BankFintech	0.401 **	0.431 **	−0.047 **	−0.052 **
	(2.167)	(2.278)	(2.281)	(2.486)
Fix	0.243	0.304	0.018	0.029
	(0.486)	(0.599)	(0.333)	(0.539)
Lev	−0.006	0.004	−0.005	−0.006
	(−0.078)	(0.056)	(−0.724)	(−0.813)
Cash	0.218 ***	0.226 ***	0.010 ***	0.011 ***
	(6.244)	(6.375)	(2.671)	(2.929)
ICR	0.614 ***	0.621 ***	−0.001	−0.000
	(16.914)	(16.786)	(−0.302)	(−0.047)
Industry-HHI		0.684		−0.021
		(1.332)		(−0.371)
BFI		45.819 ***		0.156 **
		(3.550)		(1.994)
M2		−58.138 ***		0.708 ***
		(−3.759)		(4.797)
GDP		97.357 ***		−0.683 ***
		(3.714)		(−3.498)
_cons	7.408 ***	−500.824 ***	0.723 ***	−2.756 ***
	(7.949)	(−3.495)	(7.162)	(−2.957)
Id/Year FE	YES	YES	YES	YES
Observations	3674	3607	3373	3310

Note: **, and *** represent the significance levels of 5%, and 1%, respectively. The robust standard errors are shown in parentheses. The same applies to the following tables.

5.2. Moderating Effect Test

5.2.1. Moderating Effect of Enterprise Digitalization Level

Whether the digitalization level of enterprises can influence SDLU has been examined by existing studies from two perspectives: the acquisition and use of long-term financing. From the perspective of acquiring long-term financing, the digital transformation of enterprises can achieve efficient processing and transmission of information through the application of digital technology, thereby reducing the information gap between fund suppliers and fund seekers (Fan et al., 2012), which helps to enhance the enterprise's capacity to acquire long-term funds. From the perspective of fund utilization, digital transformation can provide more decision-making information for management and strengthen internal and external supervision, thus reducing information asymmetry within the enterprise and optimizing corporate governance (Jia et al., 2024) as well as inhibiting mismatches in investment and financing tenors (Y. Y. Liu & Guo, 2023).

To further validate the governance effect of enterprise digitalization on BankFintech and SDLU, this text employs an Enterprise Digital Transformation Index constructed using data from the CSMAR database for verification. This data is based on relevant content published in annual reports, fundraising announcements, qualification recognitions, etc., by quoted companies. It reflects comprehensive application across multiple aspects including strategic guidance, technology-driven initiatives, organizational empowerment, digital application, and positive results from digitization. The data source is authoritative and reliable, capable of presenting complete and objective data related to enterprise digital transformation. Table 12 shows that the inhibiting effect of BankFintech on SDLU is more pronounced in samples with high levels of enterprise digitization (β = −0.587 **, $p < 0.05$), whereas it is not significant in samples with low levels of digitization (β = 0.342, $p > 0.1$). This tallies with a cross-explanatory framework combining signal diffusion theory with agency cost theory. The digitalization level of enterprises not only serves as a signal display for its own governance quality but also provides a technological interface for fintech supervision; their synergy reinforces governance efficacy against short-term debt being used for long-term purposes—essentially a dual empowerment in "technology-management".

Table 12. Adjustment effect of the enterprise digitalization level.

	(1) Low-Digitalization	(2) High-Digitalization
	SDLU	SDLU
BankFintech	0.342	−0.587 **
	(0.434)	(0.256)
Fix	−0.124	−0.075
	(1.169)	(0.680)
Lev	0.345 *	0.072
	(0.202)	(0.082)
Cash	0.036	−0.113 **
	(0.068)	(0.049)
ICR	−0.174 **	−0.084 *
	(0.074)	(0.050)
Industry-HHI	1.938 *	0.139
	(1.095)	(0.770)
BFI	−0.800	2.846 ***
	(1.461)	(0.998)
M2	−3.476	−0.304
	(2.471)	(1.900)
GDP	3.796	1.961
	(3.273)	(2.501)
_cons	15.119	−35.676 ***
	(20.834)	(11.642)
Id/Year FE	YES	YES
Observations	891	2424

Note: *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively. The robust standard errors are shown in parentheses. The same applies to the following tables.

5.2.2. Moderating Effect of Financial Regulatory Intensity

Financial regulation, as a crucial instrument for preventing financial risks and maintaining financial stability, has garnered significant attention from both the party and the state. The academic discourse surrounding the impact of financial regulation on bank credit allocation or enterprise development varies widely. Some scholars argue that financial regulation can positively influence credit supply by breaking monopolies and enhancing market competition in the financial market (Cypher, 1996). Conversely, other researchers point out that capital regulation has a notable inhibiting effect on the credit expansion of China's commercial banks (Q. Wang & Wu, 2012; L. Yang et al., 2020). For enterprises, financial regulation significantly curbs the financialization level of real entities through equity balance and transparent corporate governance environments (Huang et al., 2020). However, overly stringent financial regulation can impede economic growth (C. Wang & Yu, 2020). Therefore, it is not entirely certain that a higher intensity of financial regulation is always beneficial.

This paper references the research by Tang et al. (2020) and uses the proportion of financial regulatory expenditures to the added value of the local banking business at the provincial level as the financial regulatory data. Table 13 indicates that the inhibitory effect of BankFintech on SDLU is more pronounced in samples with low financial regulatory intensity (β = −0.575 **, $p < 0.05$), whereas it is insignificant in samples with high regulatory intensity (β = −0.466, $p > 0.1$). This phenomenon reveals the existence of a dynamic substitution boundary in "regulation-technology". When institutional constraints are insufficient, technological innovation becomes an essential tool for risk mitigation; under a strong regulatory environment, the deterrent effect of the system itself may weaken the marginal revenue of technological applications. This also corroborates the viewpoint of R. Wang et al. (2019) that it is challenging to maintain financial regulation at an optimal level in practice; over-regulation and under-regulation are, in reality, the norm, and China's financial regulatory intensity has not yet reached the "optimal level".

Table 13. Adjustment effect of financial regulatory intensity.

	(1) Low-Regulation	(2) High-Regulation
	SDLU	SDLU
BankFintech	−0.575 **	−0.466
	(0.273)	(0.535)
Fix	−0.484	−1.932
	(0.682)	(1.715)
Lev	−0.136	0.000
	(0.088)	(0.237)
Cash	−0.065	−0.244 **
	(0.048)	(0.114)
ICR	−0.114 **	−0.221 **
	(0.052)	(0.109)
Industry-HHI	−0.736	1.556
	(0.690)	(1.758)
BFI	0.548	5.828 ***
	(0.976)	(2.095)
M2	0.559	−4.675
	(1.880)	(3.693)
GDP	−0.250	9.860 **
	(2.460)	(5.001)
_cons	−8.355	−81.055 ***
	(11.498)	(27.318)
Id/Year FE	YES	YES
Observations	2405	910

Note: **, and *** represent the significance levels of 5%, and 1%, respectively. The robust standard errors are shown in parentheses. The same applies to the following tables.

5.2.3. Moderating Effect of Policy Shocks

Government policy guidance serves as a crucial instrument in addressing market failures within the financial sector. This study focuses on two specific policies: the “National Pilot Policy of Information Benefiting the People” and the “Pilot Policy of Combining Science and Technology with Finance” in China. The “National Pilot Policy of Information Benefiting the People”, launched by the National Development and Reform Commission in 2014, aims to leverage digital technologies to dismantle “isolated islands of information,” facilitate the integration and sharing of data resources, enhance government service quality, and ultimately benefit both citizens and enterprises (Y. K. He et al., 2024). The “Pilot Policy of Combining Science and Technology with Finance”, jointly introduced by the Ministry of Science and Technology, the People’s Bank of China, the China Banking and Insurance Regulatory Commission, and other relevant departments in December 2010, seeks to promote the integrated development of diversified financial resources, support the effective integration between technological innovation and financial systems, and alleviate financing difficulties and high costs faced by new ventures (L. Y. Ma & Li, 2019). The commonality of these policies reflects China’s strategic logic of leveraging institutional innovation to unlock digital dividends, while their differences highlight distinct pathways for digital transformation in social governance and economic domains. The Information for the People pilot emphasizes equal access to public services, whereas the Science, Technology, and Finance pilot focuses on enhancing market efficiency. Together, they form the dual pillars of “governance-market” for the digital transformation of China, holding significant research value.

This study categorizes enterprises based on their location in pilot cities versus non-pilot cities and their participation timing in the respective policies to explore the regulatory effects of these two policies on SDLU. Table 14 indicates that both policies positively regulate the inhibiting effect of BankFintech on SDLU. This phenomenon can be analyzed from three dimensions: institutional empowerment, technological diffusion, and collaborative governance.

Institutional Empowerment Mechanism: Pilot policies create a regulatory sandbox for financial technology applications through administrative licensing breakthroughs and financial support. For instance, the “National Pilot Policy of Information Benefiting the People” allows banks to access government data platforms (e.g., social security and taxation data), breaking traditional credit data silos and enabling banks to construct more precise enterprise profiles. The “Pilot Policy of Combining Science and Technology with Finance” leverages tax preferences to guide banks in directing credit funds toward enterprises that are undergoing digital transformation, forming a “technology application-risk reduction-policy incentive” virtuous cycle.

(1) Technological Diffusion Effect: Pilot policies establish technical standards and ideal practices that exhibit spillover effects. In the “National Pilot Policy of Information Benefiting the People”, government-led supply chain finance platforms (e.g., Shenzhen Financial Services Platform) standardize IoT monitoring technologies, enabling banks to deploy cargo tracking systems at a low cost, thereby directly reducing the likelihood of enterprises from misusing short-term loans for fixed asset investments. In the “Pilot Policy of Combining Science and Technology with Finance”, the “Science and Technology Financial Brain” established in Suzhou Industrial Park uses knowledge graph technology to dynamically link enterprise R&D investments with operating cash flows, providing early warnings against the risks of short-term debt used for long-term purposes.
(2) Collaborative Governance Network: Pilot policies foster cross-departmental cooperation to build new regulatory sandboxes. For example, Hangzhou’s “Financial

Technology Innovation Regulatory Pilot" during the "National Pilot Policy of Information Benefiting the People" allows banks to test smart contract fund monitoring systems in specific scenarios, balancing innovation with risk control. In the "Pilot Policy of Combining Science and Technology with Finance", the Science Branch in Chengdu High-tech Zone connects directly with the Science Bureau's data to automatically verify R&D expense deduction data with bank credit systems, thereby directly reducing corporate financial window-dressing risks.

(3) These policy-driven technological governance innovations align with path dependency theory in new institutional economics and reflect the role of "order parameters" in reconstructing financial ecosystems within complex system theory, offering a Chinese solution for financial risk management in the digital era. Future efforts should focus on strengthening cross-domain data flow mechanisms and promoting collaborative innovation in policy tools to foster a more efficient digital governance ecosystem.

Table 14. Moderating Effect of Policy Shocks.

	(1)	(2)	(3)	(4)
	National Pilot Policy of Information Benefiting the People		**Pilot Policy of Combining Science and Technology with Finance**	
	Treated	**Untreated**	**Treated**	**Untreated**
	SDLU	SDLU	SDLU	SDLU
BankFintech	−1.008 **	−0.192	−1.190 **	−0.157
	−0.509	−0.208	−0.48	−0.296
Fix	−1.374	0.532	−0.596	−0.438
	−1.223	−0.604	−1.114	−0.801
Lev	0.073	0.185 **	0.038	0.315 **
	−0.133	−0.094	−0.122	−0.151
Cash	−0.118	−0.046	−0.126	−0.009
	−0.095	−0.039	−0.088	−0.054
ICR	−0.300 ***	−0.004	−0.168 *	−0.106 *
	−0.093	−0.043	−0.089	−0.061
Industry-HHI	1.022	−1.071 *	0.445	0.279
	−1.477	−0.611	−1.343	−0.825
BFI	3.996 **	0.464	3.780 **	0.159
	−1.896	−1.447	−1.717	−1.13
M2	−3.832	1.104	−2.598	1.624
	−3.665	−1.447	−3.332	−2.109
GDP	7.737	−1.099	5.977	−1.922
	−4.858	−2.094	−4.401	−2.792
_cons	−54.813 **	−6.436	−52.329 **	−1.752
	−22.405	−24.861	−20.474	−13.426
Id/Year FE	YES	YES	YES	YES
Observations	1089	1905	1165	1274

Note: *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively. The robust standard errors are shown in parentheses. The same applies to the following tables.

6. Comprehensive Discussion

6.1. Research Conclusions

The study analyzes the data on the number of technological patents to explore the impact of BankFintech on SDLU and its mechanism of action. The research finds that BankFintech leads to a dual increase in the rate of capital sufficiency and liquidity for banks, tilting their risk preferences towards long-term financing that matches duration. Furthermore, the enhanced information-screening capabilities of banks "forces" enterprises to proactively improve their financial health and political openness. Enterprises, based on their own financing needs, enhance their ability to obtain long-term loans, achieving proactive governance of mismatched risks. Specifically, the empirical research in this text yields the following conclusions:

(1) The benchmark regression results indicate that the development of BankFintech is conducive to reducing the level of short-term debt used for long-term purposes by enterprises. Moreover, the results remain robust even after replacing the nuclear center explanatory variables with the explained variables, employing the instrumental variable method, and using PSM approximate sample matching.
(2) The heterogeneity analysis reveals that BankFintech's effects are more pronounced in non-state-owned companies and technology-intensive industries, inhibiting SDLU more effectively.
(3) The intermediary mechanism analysis shows that BankFintech enhances the rate of capital sufficiency (CAR) and liquidity ratio (Liquidity Ratio) of banks, strengthening their willingness and ability to supply long-term financing. Simultaneously, BankFintech alleviates the issue of insufficient information-screening capabilities in banks, exhibiting a "quality preference" that "forces" enterprises to proactively improve their financial health and information disclosure quality.
(4) The moderating effects indicate that the improvement in enterprise digitalization levels strengthens BankFintech's inhibiting effect on SDLU; the "National Pilot Policy of Information Benefiting the People" and the "Pilot Policy of Combining Science and Technology with Finance" policies respectively form institutional empowerment from social governance and economic governance perspectives, reducing the phenomenon of term mismatch; it is noteworthy that in samples with high financial regulation intensity, BankFintech's inhibiting effect on SDLU is not significant, reflecting that China's financial regulation intensity has not yet reached the "optimal level".

6.2. Policy Implications

To address the systematic risk arising from maturity mismatch (SDLU) in China's credit market, this study proposes a multidimensional policy framework based on empirical evidence of BankFintech mitigating short-term debt used for long-term purposes. It is recommended to implement the following measures across four territorial domains, combining heterogeneous characteristics with technical innovation to construct a differentiated financial stability mechanism:

(1) Optimize the financial regulation system and implement differentiated dynamic regulation.

Establish a "regulatory sandbox" pilot mechanism: For banks with active applications of financial technology, allow pilot testing of innovative financing products under controllable risk conditions. During the pilot period, relax the regulatory tolerance for the liquidity ratio, but require real-time monitoring of core indicators such as the rate of capital sufficiency through the central bank's regulatory technology (RegTech) system to prevent technical misuse.

Dynamically adjust the regulatory intensity threshold value: On the basis of data such as the number of financial technology patents and the improvement effect of SDLU, lay down graded regulatory standards. With regard to banks with high technical investment and significant risk control effects, reduce the frequency of on-site checks; on the other hand, strengthen window guidance to refrain from "one-size-fits-all" approaches that inhibit innovation.

(2) Targeted support for financial institutions to enhance their long-term financing supply capacity.

Implementing special incentives for "science and technology credit": providing R&D expenses and tax incentives for financial technology patents independently developed or cooperatively developed by banks, with a particular focus on supporting technology-intensive industries and the long-term lending business of non-state-owned enterprises.

Constructing a "maturity-matching" assessment mechanism: incorporating the proportion of medium- and long-term loans into the MPA (macro-prudential assessment) assessment system, prioritizing the opening of interbank certificates of deposit (CDS) issuance quota for banks whose SDLUs have fallen to the standard and allowing them to supplement their capital through the issuance of small and microfinance bonds, alleviating the pressure of maturity mismatch. Introduce supplemental capital to ease the pressure of maturity mismatch.

(3) Promoting digital transformation of enterprises and strengthening governance capabilities.

Establishment of the "Enterprise Digital Upgrade Fund": Provide purchase subsidies for small and medium-sized enterprises that procure digital tools such as financial control systems and supply chain data platforms. Require subsidized enterprises to achieve direct data connectivity with banking systems to ensure real-time sharing of financial health, cash flow forecasting, and other relevant information.

Implementation of the "Information Disclosure Quality Certification": Develop corporate information disclosure rating standards in collaboration with industry associations and third-party organizations. Enterprises meeting these standards are eligible for preferential treatment, including green channels for loan examination and approval, as well as reduced interest rates. Those failing to meet the standards face restrictions on the number of short-term loan rollovers, thereby forcing improvements in disclosure quality.

(4) Deepening policy pilot coordination to unlock institutional empowerment effects.

Integration of the "Dual Pilot" Policy Toolkit: In cities designated as "Information for the People National Pilot", mandate the opening of government data (e.g., taxation, social security) interfaces to banks to enhance corporate credit profiles. In regions designated as "Science and Technology Finance Combination Pilot", promote the "R&D Cycle-Aligned Loan", allowing enterprises to secure loans exceeding five years using technological patents as collateral, to address financing mismatches in technology-intensive industries.

Establishment of Regional "FinTech Laboratories": In regions such as the Guangdong–Hong Kong–Macao Greater Bay Area and the Yangtze River Delta, spearheaded by the central bank, form joint laboratories involving banks, tech companies, and industrial chain leaders. Develop term-matching models tailored to industry characteristics, creating replicable standardized solutions.

6.3. Research Limitations

(1) The article does not establish a more reasonable framework for measuring the materiality of enterprises' "short-term debt and long-term use".
(2) Due to the availability of data, the metrics of bank financial risk are not comprehensive enough.
(3) The conclusion of the article ignores the ethical risks of technology (e.g., AI discrimination, data privacy leakage, etc.).

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