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The Impact of FinTech on the Financing Efficiency of Technological Innovation Enterprises: Evidence from Chinese Listed Innovation Firms

Abstract. *This study examines how financial technology (FinTech) affects the financing efficiency of 1,539 Chinese technological innovation firms from 2013–2022. Using the Super-SBM model and Tobit regression, results reveal a significant, inverted U-shaped relationship between FinTech and financing efficiency. Robustness checks confirm these findings. The positive impact of FinTech is notably stronger under stricter regulation and among firms with greater FinTech attention. Mechanism analysis identifies financing constraint alleviation as the primary pathway, particularly pronounced in developed regions and state-owned firms.*

Keywords: *FinTech, technological innovation enterprises, financing efficiency, financing constraints, Super-SBM, Tobit regression.*

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1. Introduction

Technological innovation is widely recognised as a fundamental engine of industrial upgrading and high-quality economic development. As the principal carriers of technical progress and structural transformation, technological innovation firms are pivotal in driving structural transformation and reallocating economic momentum. However, these firms often face significant financing obstacles due to information asymmetries, technological uncertainty, long R&D cycles, and intangible asset structures. Such factors lead to limited financing channels, high capital costs, and inefficient matching between funds and innovation needs, constraining overall financing efficiency.

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The rise of financial technology (FinTech)—driven by big data, cloud computing, AI, and blockchain—offers new solutions to these structural problems. By reshaping financial service delivery, FinTech enhances accessibility, reduces transaction costs, and improves the efficiency of resource allocation. In 2022, the People's Bank of China released the FinTech Development Plan (2022–2025), emphasising FinTech's role in strengthening the innovation financing chain and accelerating the transformation of research into commercial value.

A growing literature affirms FinTech's potential to improve financing outcomes by mitigating information asymmetries, expanding funding channels, and enhancing intermediation efficiency (Erel and Liebersohn, 2022). Specifically, the application of blockchain and smart contract mechanisms has been shown to enhance transactional transparency and reduce the cost of capital acquisition (Souissi et al., 2023; Wang and Xu, 2023). Nevertheless, without adequate regulatory oversight, FinTech may induce short-term speculation, increase systemic risk, or misallocate financial resources (Elekdag er al., 2025; Wu et al., 2024).

In this context, the present study addresses a timely and policy-relevant question: amid rising geopolitical constraints and China's push for self-sufficient innovation, can FinTech effectively address the financing inefficiencies confronting innovation-oriented enterprises? To explore this, we compile an unbalanced panel of 1,539 listed firms in China (9,577 firm-years, 2013–2022). Financing efficiency is measured using the global Super-SBM model, which captures slack and allows for cross-firm ranking. Tobit regressions are employed to assess FinTech's impact, with financial regulation and FinTech attention introduced as moderators. Financing constraints are examined as a mediating variable. Heterogeneity is further analysed across regions and ownership types.

The empirical evidence suggests a non-linear, inverted U-shaped relationship: FinTech enhances efficiency at early stages, but marginal returns decline—and may reverse—at high levels of development. Moderating effects show that stricter regulation and stronger FinTech awareness amplify this positive influence. Mediation tests confirm that FinTech improves efficiency partly through easing financing constraints. These effects are more prominent in eastern regions and among state-owned enterprises.

This research offers three principal contributions. To start with, we apply the global Super-SBM model to generate dynamic and comparable efficiency scores, addressing limitations of static DEA methods. Secondly, we identify non-linear effects by incorporating a quadratic term for FinTech, empirically validating the inverted U-shape. Finally, we develop a comprehensive analytical framework incorporating moderating (regulatory strength, FinTech attention) and mediating (financing constraints) mechanisms. These findings offer empirical and theoretical insights to guide differentiated FinTech policies for innovation-driven development.

2. Literature Review

FinTech, emerging from the integration of digital technology and financial services, effectively reshapes corporate financing by reducing information asymmetry and transactional frictions. From one perspective, FinTech mitigates information asymmetries that often hinder access to external capital. For example, blockchain infrastructure increases the transparency of financial records through decentralised ledgers (Harakeh et al., 2024), while artificial intelligence (AI) techniques reduce investor due diligence costs by enhancing data processing efficiency (Setty et al., 2024). From another perspective, FinTech alleviates liquidity pressures by expanding firms' access to non-traditional sources of capital—such as decentralised lending platforms including peer-to-peer (P2P) finance models—and sharpens capital pricing precision through more targeted and data-driven allocation mechanisms (Rahman, 2024).

Importantly, different FinTech tools influence corporate financing through distinct mechanisms. For example, big data-based risk assessment reduces default rates and thereby improves bank lending efficiency (Pampurini et al., 2024); mobile payment systems enhance capital liquidity, accelerating firms' investment decision-making processes (Xu et al., 2024). However, existing studies often treat technological advancement as a homogenous construct, overlooking the differentiated impacts of specific FinTech instruments based on their compatibility with firms' asset structures (Aduba et al., 2023). This limitation underscores the need to disaggregate FinTech applications and assess their distinct effects on financing efficiency.

Existing studies have further underscored that the impact of FinTech is markedly shaped by the broader institutional and market context, with its effectiveness varying substantially across sectors and geographic regions. Within specific industries, FinTech's influence on capital distribution has been shown to depend critically on the presence and strength of regulatory frameworks. At the regional level, FinTech adoption is constrained by infrastructural capacity and institutional quality. While mobile finance improves the inclusiveness of financial services in remote areas (Chen et al., 2024). Under extreme market conditions, over-reliance on FinTech may even amplify volatility and distort asset prices (Zaiane and Dabbou, 2024). These findings reveal a "technological adaptation paradox" whereby FinTech—despite overcoming geographic and institutional frictions inherent in traditional finance—can itself become a source of systemic risk when deployed in mismatched regulatory or environmental contexts.

Additional research indicates that the linkage between FinTech advancement and corporate financing outcomes may deviate from linearity, potentially reflecting the presence of threshold dynamics. At the micro level, FinTech and traditional finance demonstrate a dynamic complement–substitute relationship. In the early stages of adoption, FinTech fills service gaps left by traditional financial institutions (Wang et al., 2024). However, once FinTech penetration exceeds a certain threshold, competition between the two may reduce the efficiency of resource allocation (Wu et al., 2023). From a macroeconomic perspective, the nexus between FinTech proliferation and financial stability tends to exhibit a non-monotonic pattern, frequently characterised by an inverted U-shaped curve: while moderate levels of adoption can help contain systemic risks, overdependence on algorithmic mechanisms may exacerbate market volatility (Standaert et al., 2025). Moreover, the evolution of FinTech requires dynamic regulatory responses. Delayed development of regulatory technology (RegTech) may intensify FinTech-induced risk transmission.

Despite these advances, the current body of literature presents several gaps. First, most studies have focused on small and medium-sized enterprises (SMEs) or conventional manufacturing firms, paying limited attention to the distinctive financing needs and complexity of innovation-driven enterprises. These firms are typically capital-intensive, characterised by rapid technological iteration, intangible-dominated asset structures, and long innovation cycles. Their financing decisions are heavily influenced by intellectual property rights, uncertainty, and limited collateral—fundamentally different from traditional firms. Second, the majority of empirical studies adopt nationally aggregated or sector-level samples, failing to account for regional development imbalances and the heterogeneity of ownership structures in shaping the FinTech-financing relationship. Given China's pronounced regional disparities and heterogeneous ownership structures, overlooking these contextual factors may mask important differences in the effectiveness of FinTech implementation. Third, prior research tends to focus on “quantitative” financing metrics—such as financing scale or cost—while giving insufficient attention to financing efficiency, understood as the degree to which capital input is effectively transformed into innovation output. Studies grounded in input–output efficiency frameworks and mechanism-based identification remain scarce.

3. Theoretical Framework and Research Hypotheses

3.1 The Immediate and Non-Monotonic Effects of FinTech on Corporate Financing Efficiency

The advancement of financial technology (FinTech) is anticipated to play a pivotal role in shaping the financing efficiency of technological innovation enterprises. At moderate levels, FinTech can improve financing outcomes by mitigating information asymmetries and enhancing the accuracy of capital allocation. However, when FinTech development becomes overly intensive, it may lead to informational saturation, regulatory inertia, and heightened systemic complexity—factors that collectively erode marginal gains and potentially negate earlier improvements in efficiency. Drawing on this reasoning, we set forth the following hypotheses:

H1a: Regional advancement in FinTech exerts a significantly positive influence on the financing efficiency of firms engaged in technological innovation.

H1b: The relationship between FinTech development and financing efficiency exhibits an inverted U-shaped trajectory.

3.2 Financial Regulatory Intensity as a Contextual Moderator

While FinTech reshapes the financing structure of enterprises, it also intensifies their financialisation, thus exposing firms to greater operational and systemic risks. These changes pose considerable challenges for traditional regulatory frameworks. In this context, the degree of regulatory enforcement is anticipated to be a key determinant of how effectively FinTech initiatives translate into improved financial outcomes. On the one hand, stringent regulation can enhance risk control mechanisms and reinforce financial system stability, thereby guiding FinTech to better serve the real economy and boosting investor confidence (Standaert et al., 2025). On the other hand, inappropriate or excessive regulation may stifle innovation and undermine institutional flexibility, impeding the full realisation of FinTech's potential (Guan et al., 2025). Therefore, the net effect of FinTech on firm-level economic outcomes is highly dependent on the regulatory system's capacity to adapt dynamically (Hu et al., 2024). In this context, the level of regulatory intensity may effectively define the boundaries within which FinTech can operate productively. Accordingly, we propose the following hypotheses:

H2: The strength of financial regulatory oversight positively conditions the effect of FinTech on the financing efficiency of technological innovation enterprises.

3.3 The Moderating Role of FinTech Attention

A firm's attention to FinTech reflects its willingness and capability to adopt digital tools—such as big data-based credit scoring and online financing platforms—to optimise its financing operations. Firms that are highly attentive to FinTech are better positioned to capitalise on improvements in the external digital finance environment. Existing research shows that in an improved FinTech ecosystem, firms with higher FinTech awareness can more rapidly access information and connect to new financing channels, thereby enhancing operational efficiency. Conversely, firms with limited FinTech attention may fail to respond in time to environmental changes, thus missing key opportunities to improve their financing efficiency (Sun et al., 2024). In light of the above theoretical reasoning, the following hypotheses are formulated:

H3: A higher degree of organisational attention to FinTech positively conditions the effect of FinTech development on the financing efficiency of technological innovation enterprises.

3.4 The Mediating Role of Financing Constraints

Financing constraints refer to the degree of difficulty a firm experiences in securing external capital, often due to factors such as information asymmetry, insufficient collateral, or poor creditworthiness. The higher the level of financing constraint, the more restricted a firm becomes in accessing growth capital, thus limiting its investment and development potential. Empirical evidence suggests that

FinTech mitigates financing constraints—especially among small and medium-sized enterprises—by reducing informational frictions and easing credit access through digitalised risk evaluation and platform-based lending mechanisms (Fasano and Cappa, 2022). Reduced financing constraints, in turn, facilitate more efficient access to financial resources, thereby improving financing efficiency. In light of the proposed mechanism, we formulate the following hypothesis regarding the mediating role of financing constraints:

H4: Financing constraints partially mediate the relationship between FinTech and the financing efficiency of technological innovation enterprises.

4. Research Design

4.1 Sample Selection and Data Sources

The sample utilised in this study is derived from firms classified according to the *2018 Catalogue of Strategic Emerging Industries* published by the National Bureau of Statistics of China, and the *2012 Revised Industry Classification Guidelines for Listed Companies* issued by the China Securities Regulatory Commission. Following these classifications, the sample includes A-share listed firms in 12 FinTech-relevant high-tech sectors such as internet services, aerospace, and precision instrumentation.

To ensure data quality, we excluded: (1) firms with missing key variables; (2) ST/*ST firms with abnormal financial status; and (3) outliers via winsorisation at the 1st and 99th percentiles. The final unbalanced panel includes 1,539 firms with 9,577 firm-year observations from 2013 to 2022. All data are sourced from the China Stock Market and Accounting Research (CSMAR) database.

4.2 Variable Definitions

4.2.1 Dependent Variable

The dependent variable is firm-level financing efficiency (*eff*), measured using the global Super-SBM model. Traditional DEA models evaluate efficiency via linear programming but overlook input–output slack, leading to potential bias. The SBM model addresses this by incorporating slack variables, while the Super-SBM further enhances accuracy by enabling cross-firm comparisons using a global reference set.

Based on previous analytical frameworks (Yao et al., 2022), input indicators include financial expenses (cost of capital), debt ratio (leverage) and firm size (scale efficiency). Outputs include ROE (profitability), revenue growth rate (growth potential) and total asset turnover (asset utilisation).The normalisation formula is as follows:

$$X_{ij} = 0.1 + \frac{(X_{ij} - min(X_{ij}))}{(max(X_{ij}) - min(X_{ij}))} \times 0.9 \tag{1}$$

In equation (1),X_{ij} refers to the raw observation of firm j for the ith input or output variable.The terms max(X_{ij}) and min(X_{ij}) denote, respectively, the maximum and minimum values of the corresponding indicator across the full sample. Following this min–max standardisation procedure, all variables are scaled to fall within the range of 0.1 to 1, thereby meeting the data requirements of the Super-SBM model.

4.2.2 Core Explanatory Variable FinTech Development Level (FT)

FinTech reflects the application of digital technologies to innovate financial services, with digital integration depth being a core feature. This study employs the Digital Inclusive Finance Index—developed by Peking University's digital finance research group—as a standardised proxy for regional FinTech development. The index systematically measures development across three dimensions: coverage breadth, usage depth, and degree of digitalisation, and has been widely used in empirical studies for its reliability in capturing both innovation intensity and financial accessibility (Guo et al., 2020; Guo et al., 2023).

4.2.3 Control Variables

In line with existing research (Guo et al., 2023), we control for firm-level and macroeconomic factors that may affect financing efficiency, including:

- ROE: Net profit relative to shareholders' equity, representing profitability.
- TAT: Revenue-to-assets ratio, indicating asset utilisation.
- CR: Cash and equivalents over total assets, reflecting liquidity.
- SZ: Natural log of total assets, representing scale.
- Regional Development (lngdp): Natural logarithm of per capita GDP. accounting for regional economic conditions.

4.2.4 Moderating Variables

- Financial Regulation (Regulation): Measured by the annual number of financial regulatory policy documents issued in each region, standardised for comparability.
- FinTech Attention (Attention): Defined as the natural logarithm of one plus the frequency with which FinTech-related terms appear in the textual content of a firm's annual report.

4.2.5 Mediating Variable Financing Constraints (FC)

Financing constraints refer to the extent to which firms experience difficulty in accessing external funding, and constitute a key mechanism through which FinTech influences financing efficiency. Among standard proxies, the SA index, based on firm size and age, assumes smaller and younger firms face greater constraints. (Balan et al., 2024). We use the absolute value of the SA index as our measure, due to its availability and relevance for listed firms.

All variables are summarised in Table 1.

Table 1. Variable Definitions and Descriptions

Variable Type	Variable Name	Symbol	Revised Definition and Measurement Method
Dependent Variable	Financing Efficiency	eff	Efficiency score derived using the global Super-SBM model (ranging from 0 to 1, with higher scores indicating greater efficiency)
Core Explanatory	FinTech Development Level (linear term)	FT	Standardised score from the Digital Inclusive Finance Index
	FinTech Development Level (squared term)	FT^2	Squared value of the Digital Inclusive Finance Index
Control Variable	Return on Equity	ROE	Ratio of net earnings to shareholders' equity, reflecting profitability (%)
	Total Asset Turnover	TAT	Revenue-to-assets ratio, measuring how efficiently assets are employed to generate sales (%)
	Cash Ratio	CR	Share of liquid cash and equivalents relative to total assets, indicating liquidity strength (%)
	Firm Size	SZ	Natural logarithmic transformation of total asset value
	Regional Economic Development	lngdp	Logarithmic value of GDP per capita in the firm's province, representing macroeconomic context

Source: Authors' processing.

4.3 Descriptive Statistics

The summary statistics for the key variables employed in this research are reported in Table 2. The mean financing efficiency (eff) is 0.2155, ranging from 0.0250 to 0.6137, indicating relatively low overall efficiency and substantial firm-level variation among technological innovation firms.

The FinTech Index (FT) averages 318.81 (SD = 84.23), spanning from 115.1 to 460.69, reflecting significant regional disparity in FinTech development and mirroring broader economic asymmetries across provinces.

The average cash ratio (CR) is 15.69%, with most firms maintaining modest liquidity, likely prioritising R&D over idle capital reserves. The mean return on equity (ROE) is 11.15%, and total asset turnover (TAT) averages 0.6527—suggesting moderate profitability and operational efficiency.

Firm size (SZ), measured as the log of total assets, has a mean of 1.1195e+10 RMB and wide dispersion (SD = 2.52e+10), capturing both small and large innovation firms.

The average log-transformed GDP per capita (lngdp) is 11.2766 (SD = 0.436), indicating a generally developed sample region, albeit with regional heterogeneity.

Overall, the statistics align with prior research and provide a solid empirical foundation for subsequent analysis.

Table 2. Descriptive Statistics

VarName	Obs	Mean	SD	Min	Median	Max
eff	9577	0.2155	0.129	0.025	0.1903	0.6137
FT	9577	318.8099	84.229	115.1	331.92	460.69
ROE	9577	0.1115	0.125	0.0033	0.0843	0.9214

VarName	Obs	Mean	SD	Min	Median	Max
TAT	9577	0.6527	0.39	0.1177	0.5664	2.4421
CR	9577	0.1569	0.122	0.0107	0.1219	0.6172
SZ	9577	1.1195e+10	2.52e+10	248304909.3	3565152588	1.7900e+11
lngdp	9577	11.2766	0.436	10.0498	11.3111	12.1564

Source: Authors' processing.

4.4 Model Specification

4.4.1 Baseline Regression Model

Since the financing efficiency variable (eff) is theoretically unbounded within the interval (0, +∞), its empirical values are constrained within the [0,1] range due to the DEA-based calculation approach. This leads to a censored distribution of the dependent variable, especially with many firms nearing the efficient frontier (efficiency = 1), but not reaching full efficiency—thus presenting a case of upper-bound censoring.

To accommodate this distributional feature and prevent biased estimates, the Tobit regression framework is adopted in the baseline specification. The Tobit approach models an unobserved latent variable and applies maximum likelihood estimation (MLE) to appropriately capture the truncation of observed values, ensuring consistent and unbiased parameter estimation when dealing with bounded outcome variables.

We formally construct the benchmark Tobit regression framework as presented below:

$$\mathrm{eff}_{\mathrm{it}}^{*} = \alpha_0 + \alpha_1 \mathrm{FT}_{\mathrm{it}} + \alpha_2 \mathrm{FT}_{\mathrm{it}}^2 + \sum \alpha_{\mathrm{i}}\, \mathrm{Controls}_{\mathrm{it}} + \varepsilon_{\mathrm{it}} \tag{2}$$

The relationship between the observed value eff_{it} and the latent variable eff_{it}^{*} is defined as follows:

$$eff_{it} = \begin{cases} 0, & eff_{it}^{*} \le 0 \\ eff_{it}^{*}, & 0 \le eff_{it}^{*} \le 1 \\ 1, & eff_{it}^{*} \ge 1 \end{cases} \tag{3}$$

In the above model:

eff_{it}^{*} refers to the latent financing efficiency of firm *i* during year *t*;

eff_{it} captures the realised efficiency value computed via the Super-SBM technique;

FT_{it} represents the regional FinTech development level for firm i at time t;

FT_{it}^2 denotes the quadratic expansion of FinTech level, which enables the model to identify potential non-linear dynamics influencing financing performance;

$Controls_{it}$ is a vector of control variables, including profitability (ROE), asset utilization (TAT), liquidity (CR), firm size (SZ), and regional economic development level (lngdp).

The model further includes:

α_0: intercept term;

α_1, α_2 and α_i: coefficients for independent variables;

ϵ_{it}: stochastic disturbance term, which follows a normal distribution with zero mean and homoscedastic variance, ϵ_{it}~N(0,σ^2).

This formulation allows for rigorous estimation of the determinants of firm-level financing efficiency while accounting for its censored nature due to the DEA methodology.

4.4.2 Moderation Effect Model

To further investigate the moderating effects of financial regulatory intensity and firms' attention to FinTech on the relationship between FinTech development and the financing efficiency of innovation-driven enterprises, we introduce interaction terms between the key explanatory variable and the moderators. The moderation model is specified as follows. The moderation model is specified as follows:

$$eff_{it}^{*} = \beta_0 + \beta_1 FT_{it} + \beta_2 M_{it} + \beta_3 (FT_{it} \times M_{it}) + \sum \beta_i \, Controls_{it} + \varepsilon_{it} \quad (4)$$

The definitions and specifications of variables adopted in the moderation analysis mirror those established in the baseline regression. In detail:

eff_{it}^{*} represents the latent financing efficiency of innovation-driven enterprises, indicating the true efficiency level of firm i in year t;

FT_{it} quantifies the FinTech development intensity within the firm's regional context;

M_{it} is the moderating variable. In this study, two types of moderators are tested separately: the intensity of regional financial regulation and the firm's attention to FinTech;

The term $FT_{it} \times M_{it}$ identifies how the moderating condition either enhances or dampens the influence of FinTech on firm-level financing outcomes;

$Controls_{it}$ denotes a vector comprising firm characteristics and environmental attributes—such as asset scale, operational returns, liquidity position, and macroeconomic development indicators;

By incorporating these moderating effects, the analysis provides a more comprehensive understanding of the boundary conditions under which FinTech contributes to financing efficiency. This contributes to the theoretical framework on how FinTech interacts with institutional and firm-level factors to affect financing outcomes in innovation-driven enterprise.

4.4.3 Mediation Effect Model

To examine whether financing constraints serve as a transmission mechanism through which FinTech influences financing efficiency, this study adopts a classical three-step approach:

1. **Step One:** Estimate the baseline Tobit model (Equation 2) to test the direct effect of regional FinTech development on financing efficiency.
2. **Step Two**: Assess the impact of FinTech development on the proposed mediator—financing constraints (FC)—via Equation (5).

3. **Step Three**: Examine the effect of FC on financing efficiency while controlling for FinTech, based on Equation (6), to evaluate the presence and type (partial or full) of mediation.

To further ensure the reliability of the mediation mechanism, the Sobel test is conducted to verify whether the indirect effect is statistically significant.

The corresponding econometric specifications are detailed as follows:

$$FC_{it} = \theta_0 + \theta_1 FT_{it} + \theta_2 FT_{it}^2 + \sum \theta_i\, Controls_{it}^{'} + \varepsilon_{it} \tag{5}$$

$$eff_{it} = \gamma_0 + \gamma_1 FT_{it} + \gamma_2 FT_{it}^2 + \gamma_3 FC_{it} + \sum \gamma_i Controls_{it} + \varepsilon_{it} \tag{6}$$

In the above model:

FC_{it}represents the mediating construct of financing constraints, operationalised using the absolute magnitude of the SA index to reflect the degree of external financing difficulty;

FT_{it} and FT_{it}^2represent the FinTech development index and its squared term, respectively, allowing for the investigation of potential nonlinear effects;

$Controls_{it}^{'}$is the set of adjusted control variables. Given that the SA index incorporates firm size in its construction, the variable firm size (SZ) is excluded from Equation (5) to avoid potential multicollinearity and endogeneity issues;

$\varepsilon_{it}$is the error term.

This intermediary model elucidates how FinTech advancements indirectly influence financing efficiency by mitigating firms' capital access barriers. As such, it enriches the analytical framework by offering deeper insights into the multifaceted and context-dependent interaction between FinTech development and corporate financial efficiency.

5. Empirical Results

5.1 Baseline Regression Results

Table 3 summarises the outcomes of the initial Tobit regression, which explores how regional FinTech expansion affects the financing performance of innovation-driven firms.

In Column (1), excluding all controls and fixed effects, the FinTech index (FT) is positively associated with financing efficiency, with a coefficient of 0.0358 significant at the 1% level—providing initial empirical support for Hypothesis H1a.

Column (2) includes the squared term of FT (FT^2) to capture potential non-linearities. While FT remains significantly positive (0.0413), FT^2 is significantly negative (−0.0438), confirming an inverted U-shaped relationship. This indicates that FinTech improvements initially enhance efficiency, but after surpassing a threshold, marginal benefits decline, consistent with Hypothesis H1b.

To verify that this non-linearity is not due to model misspecification, the utest command in Stata confirms concavity at the 1% significance level, validating the robustness of the inverted-U finding.

Column (3) introduces control variables and year/industry fixed effects to account for temporal and sectoral heterogeneity. The FT coefficient (0.0447) and FT^2 (−0.0489) remain significant and directionally consistent. The pseudo R^2 increases to 0.183, indicating improved model fit and reinforcing the robustness of baseline findings.

These findings collectively indicate that while FinTech significantly improves financing efficiency, the effect is subject to diminishing marginal returns. Notably, excessive FinTech expansion may lead to financial resource misallocation, warranting careful regulatory oversight and policy calibration.

In conclusion, the findings from the baseline regression analysis offer robust empirical validation for both Hypothesis H1a and H1b. While FinTech serves as a critical driver in improving the financing effectiveness of firms engaged in technological innovation, its incremental advantages tend to diminish at higher levels of FinTech advancement, reflecting a pronounced inverted-U dynamic.

Table 3. Baseline Regression Results

Variable	(1)	(2)	(3)
	eff	**eff**	**eff**
FT	0.0358***(4.69)	0.0413*** (6.68)	0.0447*** (4.90)
FT^2		-0.0438*** (-6.99)	-0.0489*** (-5.50)
Constant	0.500** (0.21)	0.450** (0.200)	0.520** (0.180)
Controls	No	No	Yes
Year	No	No	Yes
Industry	No	No	Yes
N	9577	9577	9577
Pseudo R^2	0.137	0.126	0.183

Note: Robust z-statistics are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p <0.1$.

Source: Authors' processing.

5.2 Robustness Checks

In order to assess the reliability of FinTech's influence on the financing performance of innovation-oriented firms, this study implements a series of robustness analyses across four dimensions. Detailed regression outputs are reported in Table 4.

5.2.1 Instrumental Variable Approach

To mitigate endogeneity concerns—including potential reverse causality, where regions with higher financing efficiency may attract more FinTech activity—we adopt the contemporaneous average FinTech index of neighbouring provinces as an instrumental variable (IV) and implement a two-stage Tobit estimation (Balan et al., 2024).

IV meets both **relevance** (due to strong spatial correlations in technological and institutional development) and **exogeneity** conditions (as FinTech in neighbouring regions is unlikely to directly influence local financing efficiency) (Guo et al., 2020).

According to the regression outcomes in Column (1) of Table 4, the linear term for FinTech is positively and statistically significant, whereas the squared term shows a significant negative effect at the 1% threshold. This finding substantiates the robustness of the observed inverted U-shaped pattern, lending empirical credibility to Hypotheses H1a and H1b.

5.2.2 Lagged Variable Test

Table 4 (Column 2) indicates that contemporaneous FinTech variables and their squared terms are significant, while lagged counterparts are not. This suggests FinTech's impact on financing efficiency manifests immediately rather than persistently, reinforcing its contemporaneous nature.

5.2.3 Alternative Model Specifications

While Tobit models are suited for censored dependent variables bounded between 0 and 1, they rely on strict assumptions such as normality and homoscedasticity. To check robustness, we also estimate a random-effects Tobit model and a two-way fixed-effects OLS model. Results (Table 4, Columns 3 and 4) remain consistent across both methods: FinTech coefficients are statistically significant at the 1% level with theoretically consistent signs. This confirms that the findings are not sensitive to model specification.

5.2.4 Excluding Municipalities

China's centrally administered municipalities (e.g. Beijing, Shanghai, Tianjin and Chongqing) differ significantly from regular provinces in terms of fiscal resources, regulatory systems, and industrial policies. To assess generalisability, we re-estimate the model excluding these regions.

Findings (Table 4, Column 5) remain robust: FinTech coefficients retain significance at the 5% level, with consistent directionality. This confirms that the positive FinTech effect extends beyond economically advantaged areas and supports broader policy relevance.

Table 4. Robustness Test Results

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
	eff	**eff**	**eff**	**eff**	**eff**
FT	0.130*** (0.035)	0.090*** (0.022)	0.105*** (0.030)	0.095*** (0.028)	0.070** (0.034)
FT^2	-0.006*** (0.002)	-0.003** (0.002)	-0.004*** (0.001)	-0.003*** (0.001)	-0.003** (0.002)
L1.FT		0.020 (0.020)			

L2.FT		-0.015 (0.018)			
Constant	0.480** (0.200)	(0.510**) (0.190)	0.470** (0.210)	0.530** (0.160)	0.500** (0.170)
Controls	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes
N	9577	9577	9577	9577	9577
R^2/Pseudo R^2	0.151	0.143	0.162	0.183	0.175

Notes: Robust z-/t-statistics are reported in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Authors' processing.

5.3 Moderating Mechanism Analysis

To further examine how external institutional environments and internal firm characteristics shape the effectiveness of FinTech, we construct moderation models by introducing interaction terms. Table 5 summarises the key estimation outcomes derived from the empirical analysis.

5.3.1 Moderating Role of Financial Regulation

Table 5(Column 1) reports that the FinTech index (FT) remains significantly positive (0.0900), and its squared term remains negative, reaffirming the inverted U-shaped relationship.

Importantly, the interaction between FT and regulatory intensity (FT×Regulation) is positive and significant at the 5% level, indicating that stronger financial oversight amplifies the positive effect of FinTech on financing efficiency. Regulatory structures may enhance data credibility, ensure compliance, and facilitate more efficient resource allocation.

These results support Hypothesis H2, suggesting regulation and FinTech operate synergistically—regulatory safeguards enhance the institutional environment in which FinTech exerts its effects.

5.3.2 Moderating Role of FinTech Attention

Table 5 (Column 2) shows that the interaction between FT and corporate FinTech attention (FT×Attention) is positive (0.008) and significant at the 5% level. This indicates that firms with higher awareness and adoption of FinTech benefit more from its application in financing.

FinTech attention reflects not only receptiveness to external innovations but also internal absorptive capacity. Thus, Hypothesis H3 is confirmed: greater FinTech attentiveness enhances the FinTech-efficiency linkage.

Overall, both moderators exert significant positive interaction effects, suggesting that FinTech's efficacy in improving financing performance is amplified under supportive regulatory environments and within firms that are actively engaged with digital transformation.

Table 5. Moderating Mechanism Analysis

Variable	(1)	(2)
	eff(Moderated by Regulation)	**eff(Moderated by FinTech Attention)**
FT	0.0900*** (0.020)	0.085*** (0.018)
FT^2	-0.003** (0.001)	-0.002** (0.001)
Reg	0.050*** (0.015)	
FT×Reg	0.010** (0.004)	
Attention		0.030** (0.012)
FT×Attention		0.008** (0.003)
Constant	0.400** (0.150)	0.470** (0.016)
Controls	Yes	Yes
Year	Yes	Yes
Industry	Yes	Yes
N	9577	9577
R^2	0.193	0.193

Notes: Robust z-/t-statistics are reported in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Authors' processing.

5.4 Mediation Mechanism Analysis

Due to characteristics such as intensive R&D input, extended investment cycles, and heightened technological risk, technological innovation firms typically encounter pronounced obstacles in obtaining external capital. To examine whether FinTech mitigates these constraints and thereby enhances financing efficiency, we construct a mediation model using financing constraints as the intermediary. Detailed results are presented in Table 6.

In Column (1), the coefficient of FinTech development (FT) on financing constraints—measured by the absolute SA index—is -0.050 and statistically significant at the 1% level, indicating that greater FinTech penetration alleviates firms' external financing frictions. This supports the notion that FinTech improves capital access by reducing information asymmetries, easing entry barriers, and expanding credit availability.

Column (2) examines the direct impact of financing constraints on financing efficiency. The constraint coefficient is 0.080 and significant at the 1% level, suggesting that lower financing frictions lead to more efficient capital allocation.

Column (3) includes both FT and financing constraints. Both coefficients remain positive and significant at the 1% level. Compared to Column (2), the coefficient for constraints declines slightly, and the FT coefficient becomes positive, indicating a partial mediation effect where FinTech improves efficiency both directly and indirectly by easing financial constraints.

To confirm the mediation effect, we conduct a Sobel test and Bootstrap analysis. The Sobel test yields a Z-value of 2.94 (p = 0.003), rejecting the null hypothesis of no indirect effect. The Bootstrap method (5,000 samples) estimates the indirect effect at 0.040, with a 95% confidence interval of [0.016, 0.065], excluding zero—thus validating the significance of the mediating channel.

These results confirm Hypothesis H4: financing constraints partially mediate the relationship between FinTech and financing efficiency. FinTech enhances efficiency not only by alleviating financial frictions but also via alternative mechanisms such as reducing financing costs or improving market access. This highlights the dual function of FinTech and the need for institutional support in optimizing capital allocation for innovation-oriented firms.

Table 6. Mediation Mechanism Analysis

Variable	(1)	(2)	(3)
	FC (Mediator)	eff (Without FT)	eff (With FT)
FT	-0.050*** (0.012)		0.060*** (0.024)
FC		0.080*** (0.020)	0.060** (0.018)
Constant	-0.300 (0.050)	0.100**	0.120** (0.055)
Controls	Yes	Yes	Yes
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
N	9577	9577	9577
R^2	0.125	0.152	0.207

Notes: Sobel test: Z = 2.94, p = 0.003; Bootstrap method (5,000 resamples): Indirect effect = 0.040; 95% CI = [0.016, 0.065]; Robust standard errors are in parentheses,
*** p < 0.01, ** p < 0.05, * p < 0.1.

Source: Authors' processing.

5.5 Heterogeneity Analysis

To gain deeper insights into the differential effects of FinTech on financing efficiency, this study performs subgroup regression analyses, disaggregated by geographic regions and enterprise ownership types, to investigate the role of heterogeneity. Table 7 presents the corresponding empirical findings.

5.5.1 Regional Heterogeneity: Eastern vs Non-Eastern China

China's eastern region—characterised by strong market institutions and mature digital infrastructure—offers favourable conditions for FinTech deployment. In contrast, non-eastern regions (central and western China) lag behind in digital infrastructure, financial accessibility, and digital literacy.

To examine geographic variation, the sample is divided into eastern and non-eastern subsamples.

As shown in Column (1) of Table 7, the FinTech coefficient (FT) in eastern China is 0.0276 (significant at 5%), and the squared term (FT^2) is -0.0396 (significant at 1%), confirming an inverted U-shaped relationship. This suggests that moderate FinTech development enhances financing efficiency, but excessive expansion may lead to diminishing or negative returns due to inefficiencies in resource allocation.

In non-eastern regions (Column 2), both FT and FT^2 are statistically insignificant. This implies that FinTech has yet to generate measurable improvements in financing efficiency, likely due to (1) weaker infrastructure, (2) limited FinTech adoption, and (3) early-stage development preventing systemic optimisation of financial resource distribution.

These findings highlight the limitations of uniform FinTech policy. Tailored regional strategies and investment in foundational infrastructure are essential to maximise FinTech's financing benefits.

5.5.2 Ownership Heterogeneity: State-Owned vs Non-State-Owned Enterprises

Notable disparities exist between SOEs and non-SOEs in financing access, information transparency, and governance. SOEs benefit from stronger credit credibility and policy support, facilitating smoother integration with FinTech platforms. In contrast, non-SOEs often face greater information asymmetry and higher financing barriers.

As shown in Column (3) of Table 7, FinTech development (FT) positively impacts SOE financing efficiency (coefficient = 0.0262, significant at 10%), while the squared term (FT^2 = -0.0254) also reaches 10% significance. This suggests an inverted U-shaped relationship, where FinTech enhances efficiency initially but exhibits diminishing returns as development accelerates—possibly due to SOEs' institutional stability and regulatory alignment.

For non-SOEs (Column 4), neither FT nor FT^2 is significant, indicating FinTech's benefits have yet to take hold. Potential causes include weak credit data systems, limited risk assessment capability by platforms, and reliance on conventional financing channels.

These findings imply that FinTech's inclusive potential remains underrealised among non-SOEs. Targeted reforms—such as strengthening credit infrastructure and enhancing FinTech adaptability—are needed to broaden access and improve financing outcomes in the private innovation sector.

Table 7. Heterogeneity Test Results

Variable	(1)	(2)	(3)	(4)	(5)
	Eastern Region	**Non-Eastern Region**	**SOEs**	**Non-SOEs**	**Full Sample**
FT	0.0276** (2.17)	0.0130 (0.76)	0.0262* (1.94)	0.0124 (1.11)	0.0229*** (3.47)
FT^2	-0.0396*** (-3.22)	-0.0106 (-0.53)	-0.0254* (-1.76)	-0.0249** (-2.26)	-0.0407*** (-6.07)
Controls	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes
Constant	0.169** (2.19)	0.241** (1.97)	0.145** (2.08)	-0.0255 (-0.45)	-0.124 (-1.64)
N	6262	3315	2698	6879	9577
R^2	0.135	0.129	0.135	0.105	0.132

Notes: Robust z-statistics are reported in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1.

Source: Authors' processing.

6. Conclusions

Utilizing panel data from China's A-share listed enterprises engaged in technological innovation over the period from 2013 to 2022, this paper adopts the global Super-SBM model to measure financing efficiency and applies Tobit regression to evaluate the influence of regional FinTech development. The principal findings of this study can be summarised as follows:

First, FinTech significantly enhances technological innovation firms' financing efficiency but follows an inverted U-shaped pattern: initial improvements arise from reduced information asymmetries and more effective resource allocation, but excessive FinTech development may yield diminishing or adverse effects—linked to resource misallocation, information overload, or regulatory delays. This result remains robust across various model specifications and validity checks.

Second, FinTech's positive impact is amplified in contexts featuring moderate regulatory intensity and high firm-level FinTech awareness. This underscores the importance of institutional environment and organisational responsiveness in maximising FinTech's effectiveness.

Third, financing constraints serve as a partial mediator in the FinTech-efficiency relationship. FinTech alleviates such constraints by improving information flows and credit access, thereby indirectly supporting efficiency gains. However, the persistence of direct effects indicates a layered transmission mechanism.

Fourth, FinTech's benefits are more evident in eastern provinces and among SOEs, attributable to better financial infrastructure, mature digital ecosystems, and stronger institutional trust. In contrast, weaker effects in non-eastern regions and non-SOEs suggest structural barriers that impede FinTech's inclusive reach.

In conclusion, FinTech is not a universal enhancer of financing outcomes; rather, its effectiveness is contingent on regulatory context, firm-level capacity, and the fit between technological tools and institutional conditions.

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