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Original Paper

Fin-tech Development and Corporate Financing Constraints: Evidence from the Debt Cost Channel

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Abstract

Using a panel of Chinese A-share listed firms from 2011 to 2020, matched with the Peking University Digital Financial Inclusion Index at the prefecture-city level, this paper examines whether fin-tech development eases corporate financing constraints and through which channels. In the specification with firm and year fixed effects, fin-tech development is significantly associated with a lower KZ index. This finding remains significant when standard errors are clustered at the city level, where fin-tech development varies.

The mediation analysis shows that fin-tech development significantly lowers firms' debt costs and that lower debt costs, in turn, ease financing constraints. Once debt cost is included, the direct effect of fin-tech is no longer statistically significant, which is consistent with full mediation. Fin-tech development is also associated with local bank competition, but this channel does not significantly reduce financing constraints. The results remain robust after excluding financially distressed firms and firms in the financial and real estate industries, as well as under a coarser specification with industry and year fixed effects. The evidence is weaker when the SA index is used because firm fixed effects leave little variation within firms for identification. Overall, the results identify debt cost, rather than bank competition, as the main channel through which fin-tech development eases corporate financing constraints.

1. Introduction

Financing constraints remain a persistent problem for non-financial firms, particularly in emerging markets, where credit often flows disproportionately to large, state-affiliated, or asset-rich borrowers. China's financial system has long been dominated by banks, and this characteristic precisely illustrates the aforementioned issue. State-owned banks are burdened with the tough task of risk control, while also having to deal with the costs associated with pre-loan investigations and post-loan supervision. Therefore, they naturally tend to use high-standard mortgage requirements and strict credit records to reduce their own risks. However, this approach actually causes disadvantages for small and medium-sized enterprises, private enterprises, and those start-up companies lacking credit accumulation. In the end, financial institutions hold abundant liquidity, but the enterprises that truly need funds to expand production are still unable to obtain the necessary financial support.

Fin-tech developments could go some way toward correcting this imbalance. Techniques such as big-data analysis and ML-driven scoring systems reduce the costs of gathering and digesting borrower information. In addition, blockchain-based contract execution and algorithmic matching make it easier to align credit providers with funding seekers. With these tools, financial firms can evaluate risk more accurately and offer loans under softer conditions. A growing empirical literature generally finds that fin-tech development is associated with lower financing constraints at the firm level. Less is known about the mechanisms behind this relationship.

Two questions are especially relevant. First, bank competition and lower debt costs have both been proposed as channels through which fin-tech may ease financing constraints. Few studies, however, test both channels in the same framework using independently constructed measures and bootstrap-based mediation inference rather than the increasingly outdated Sobel test. Second, the relative importance of the two channels remains unclear. Fin-tech may work mainly by lowering the price of credit, or its effect may operate through changes in the structure of local credit markets.

This paper examines both possibilities. We match a sample of Chinese A-share listed firms with the Peking University Digital Financial Inclusion Index at the prefecture-city level. We also construct a city-level measure of bank competition from the universe of bank branch registration records. This design enables us to test whether the development of fin-tech has alleviated the financing constraints of enterprises, and to directly compare the debt cost channel with the bank competition channel.

This paper makes contributions to the literature in four aspects. First, the main explanatory variable is the Digital Finance Inclusiveness Index of Peking University, which has been widely verified and is generally regarded as an authoritative indicator for measuring the development of fin-tech in China's regions.

Second, following Jiang et al. (2019), we construct the bank-competition index independently from branch data, avoiding construct-validity issues. Third, mediation analysis shows debt costs are the main channel through which fin-tech eases financing constraints, offering policy guidance. Fourth, robustness tests with industry fixed effects and gradual variable inclusion identify drivers of the weakened direct fin-tech effect; a partial-correlation test makes severe collinearity an unlikely explanation and suggests that the attenuation is more consistent with omitted-variable bias in the less complete specification. This comparison motivates our choice of firm fixed effects to control unobserved heterogeneity—a diagnostic often overlooked in fixed-effect model reporting.

2. Literature Review and Hypotheses Development

2.1 Fin-tech Development and Corporate Financing Constraints

Traditional financial intermediaries often misallocate funds, leaving some firms credit-constrained while liquidity idles within the system. Fin-tech can ease this via two routes: improving credit–demand matching through big data and machine learning, and accelerating financing via smart contracts and blockchain to cut administrative delays. Online platforms (e.g., P2P lending, crowdfunding, supply-chain finance) further broaden access by linking household savings to firm borrowing. If fin-tech reduces time and cost of external finance, firms should face fewer constraints. We therefore propose:

Hypothesis 1 (H1): Fin-tech development alleviates corporate financing constraints.

2.2 Mechanism I: Bank Competition

Large state-owned banks dominate China's credit market. Their strict risk control and cumbersome approval processes are beneficial to borrowers with substantial funds, adequate guarantees, and close ties to the government, but they exclude enterprises with weak financial conditions or insufficient guarantees. Fin-tech may break this situation by intensifying bank competition: digital services prompt traditional banks to enhance efficiency and customer experience, while new intermediaries drive supply diversification. Under competitive pressure, traditional banks constantly innovate, strengthen credit assessment, reduce information asymmetry, and accelerate approval processes, thereby expanding customer coverage and launching customized products. These changes will benefit enterprises that previously had difficulty accessing financial services, as banks have relaxed requirements for guarantees and simplified approval procedures. Therefore, easier access to credit should help reduce financing constraints. We therefore propose:

Hypothesis 2 (H2): Fin-tech development alleviates corporate financing constraints by intensifying bank competition.

2.3 Mechanism II: Debt Cost

Fin-tech expands the information sources of lending institutions from traditional financial statements to operational records, supply chain data, and internal and external information, thereby reducing information asymmetry and achieving a more comprehensive credit assessment. By identifying patterns and dynamically updating estimates, machine learning models further optimize risk identification and pricing, enabling lending institutions to set risk-adjusted interest rates more accurately. This not only enhances the institutions' risk management capabilities but also provides enterprises with fairer financing conditions. Lower debt costs subsequently alleviate financial pressure: reduced interest expenses increased net profits, releasing internal funds for investment or debt repayment, improving the capital structure, and helping to obtain higher credit ratings, thereby facilitating external financing. Thus, fin-tech enhances assessment capabilities and reduces debt costs, alleviating financing constraints. Therefore, we propose:

Hypothesis 3 (H3): Fin-tech development alleviates corporate financing constraints by reducing firms' debt costs.

3. Research Design

3.1 Sample and Data Sources

Our sample comprises Chinese A-share listed firms from 2011 to 2020, with firm-level financial and governance data drawn from a CSMAR-based panel. Local fin-tech development is measured by the Peking University Digital Financial Inclusion Index (PKU-DFIIC) at the prefecture-city level (Guo et al., 2020). Bank competition is constructed from CSMAR's branch registration database, which tracks branch approval and exit dates. Regional financial development combines city-level GDP and the same branch data. Each firm-year observation is matched to its registered city's corresponding measures, yielding an initial panel of 27,818 observations for about 3,400 firms. Our preferred specification includes firm and year fixed effects (see Section 3.3). Firms appearing only once are dropped as singletons, resulting in a baseline sample of 23,002 firm-year observations for 3,138 firms.

3.2 Variable Definitions

Dependent variable. We measure financing constraints using the KZ index. The construction follows Kaplan and Zingales (1997), as adapted to Chinese listed firms by Tan and Xia (2011) and Wei, Zeng, and Li (2014). The index is based on five firm-level variables. Operating cash flow, cash dividends plus interest paid, and cash holdings are each scaled by total assets from the *prior year*, consistent with the convention used in this literature. The leverage ratio, defined as total liabilities divided by total assets, and Tobin's Q are calculated using contemporaneous total assets.

We first construct an ordinal score ranging from 0 to 5. Within each year, firms are divided at the median of each component, and the component scores are signed so that a higher total indicates tighter financing constraints. We then regress this ordinal score on the five underlying continuous variables using an ordered logistic model. The fitted linear index, excluding the estimated cutpoints, serves as the continuous KZ index. Higher values indicate greater financing constraints. As a robustness check, we also use the SA index developed by Hadlock and Pierce (2010). Unlike the KZ index, the SA index is constructed independently of firms' cash flow and leverage.

Core independent variable. Fin-tech development (*lnFintech*) is measured as the natural logarithm of the aggregate PKU Digital Financial Inclusion Index for the firm's prefecture-level city in year *t*. For robustness, we construct an alternative proxy equal to the natural logarithm of the cumulative number of registered fin-tech companies in the firm's city of operation.

Mediating variables. Bank competition (*bankcomp*) is defined as one minus the Herfindahl-Hirschman Index of bank branch shares in each city-year, following Jiang et al. (2019). We calculate the HHI from the universe of bank branch approval and exit records in CSMAR's bank-institution database. The calculation is restricted to deposit-taking institutions: policy banks, large state-owned commercial banks, joint-stock commercial banks, city and rural commercial banks, rural credit cooperatives, postal savings banks, foreign banks, village banks, and private banks. Non-bank financial institutions, including trust companies, financial leasing companies, and consumer finance companies, are excluded. A branch is classified as active in a given year if its approval date falls before the end of that year and its exit date, where applicable, falls after year-end. Debt cost (*DebtCost*) is measured as financial expenses divided by total liabilities, a standard proxy for the average cost of debt financing in studies of Chinese firms.

Control variables. The control set follows the existing literature and includes firm size (*size*), measured as the logarithm of total assets; profitability (*roa*), measured by return on assets; asset tangibility (*tang*); ownership concentration (*top1*), measured as the ownership share of the largest shareholder; firm age (*lnage*), measured as the logarithm of years since listing; and asset growth (*tagr*), measured as the growth rate of total assets. We also control for regional financial development (*lnFir*), defined as the logarithm of the ratio of a city's total bank branches to its GDP. This variable captures the maturity of the local financial market separately from fin-tech penetration.

Cash holdings, leverage, and Tobin's Q are excluded from the control set when KZ is the dependent variable because they are structural components of the KZ index. Including them as controls would create a mechanical relationship with the dependent variable rather than provide meaningful adjustment.

Our preferred specification includes firm and year fixed effects. For comparison, Section 4.2.1 reports estimates using industry fixed effects based on the CSRC 2012 classification, together with year fixed effects. Unless stated otherwise, standard errors are clustered at the firm level.

3.3 Model Specification

Baseline model (H1). Our preferred specification includes firm and year fixed effects:

$$KZ_{i,t} = \beta_0 + \beta_1\, lnFin - tech_{c,t} + \sum \beta_2\, Controls_{i,t} + \sum Year_t + \sum Firm_i + \varepsilon_{i,t}$$

where *i* indexes firms, *c* indexes the firm's city of operation, and *t* indexes year. Firm fixed effects non-parametrically account for all time-invariant differences across firms, including unobserved factors that a broad industry classification cannot capture. A negative and statistically significant β_1 supports H1.

Mediation models (H2, H3). We examine the mediating roles of bank competition and debt cost using a two-equation model. Indirect effects are evaluated through 1,000 to 2,000 cluster-bootstrap replications at the firm level, rather than through the causal-steps procedure and Sobel tests:

$$M_{c,t} = \alpha_0 + \alpha_1 lnFintech_{c,t} + Controls_{i,t} + FE + \nu_{i,t}$$

$$KZ_{i,t} = \gamma_0 + \gamma_1\, lnFintech_{c,t} + \gamma_2\, M_{c,t} + Controls_{i,t} + FE + \varepsilon_{i,t}$$

where M denotes, respectively, *bankcomp* (H2) and *DebtCost* (H3). The indirect effect is given by $\alpha_1 \times \gamma_2$, and its significance is evaluated using the bootstrap percentile confidence interval. Consistent with recent methodological guidance (Zhao, Lynch, and Chen, 2010), we do not require the total or direct effect of *lnFintech* to be significant as a precondition for testing the indirect effect.

Robustness checks. We further assess the robustness of our findings by (i) replacing *KZ* with the *SA* index; (ii) replacing *lnFintech* with the alternative registration-count-based fin-tech measure; (iii) excluding firms in the financial and real-estate industries; and (iv) excluding ST and *ST firms.

4. Empirical Results

4.1 Descriptive Statistics

Table 1. Descriptive Statistics

	(1)				
	count	mean	sd	min	max
Financing constraint	23556	.9857283	2.022371	-4.99467	6.211571
Fintech development	27818	5.308054	.4178099	3.976686	5.77345
Bank competition	27818	.9128628	.0314458	.7876615	.9527161
Debt cost	25877	.0057482	.0399139	-.2087583	.0702644
Firm size	26216	22.12068	1.456596	19.29278	27.24757
Return on assets (ROA)	27817	.0423895	.0690348	-.298469	.232422
Asset tangibility ((fixed assets + inventory) / total assets)	25664	.3562401	.183969	.0078975	.8048231
Ownership concentration (largest shareholder's stake, %)	26199	34.63752	15.05111	8.52	74.82
Firm listing age (ln(year − listing year))	25873	2.040047	.9261318	0	3.258097
Asset growth rate	26215	.2101795	.4106096	-.35366	2.513534
Regional financial development (ln)	27768	-.7471527	.4820236	-1.693473	.4709252

The descriptive statistics are broadly consistent with those reported in earlier studies of Chinese listed firms. The KZ index has a mean close to 1 and a standard deviation of about 2. Financing constraints therefore vary substantially across firms and over time rather than clustering within a narrow range. This dispersion provides the variation used in the panel regressions reported in Section 4.2.

The main explanatory variable, *lnFintech*, has a mean of approximately 5.3 and a standard deviation of about 0.42 over the 2011 to 2020 sample period. The underlying PKU index increased almost monotonically in nearly all prefecture-level cities during these years. Much of the observed variation is therefore temporal and reflects the broad expansion of digital financial inclusion across China. Persistent differences also remain across cities, as the pace and extent of that expansion varied with city size and level of development.

DebtCost averages well below 1 percent of total liabilities. As discussed in Section 3.2, this modest value follows partly from the way the variable is constructed and should not be interpreted as evidence that firms face unusually low borrowing costs. The denominator includes total liabilities, which for most firms contain substantial non-interest-bearing items such as accounts payable, advances from customers, and accrued expenses. The ratio therefore understates the effective interest rate on interest-bearing debt.

The bank-competition measure, $bankcomp(1 - \mathrm{HHI})$ is concentrated within a relatively narrow range near 1. Most Chinese prefecture-level cities contain branches from several types of financial institutions, including state-owned banks, joint-stock banks, city commercial banks, and rural financial institutions. Consequently, no single institution typically holds a dominant share of the local market. The more informative variation lies in the lower tail of *bankcomp*, where smaller or less-developed cities tend to have more concentrated banking markets.

Firm size, profitability, asset tangibility, ownership concentration, listing age, and asset growth have distributions consistent with the broader empirical literature on Chinese A-share firms. The pairwise correlation matrix, available on request, contains no correlation among the control variables that exceeds conventional thresholds of concern. The variance inflation factors reported with Table 1 support the same conclusion, as all remain well below 2.

One correlation deserves attention before the regression results are presented. The raw correlation between *roa* and *KZ* is -0.45. This relationship is expected because the KZ index includes operating cash flow, which is closely related to accounting profitability even though the two concepts are distinct. It also anticipates the results in Section 4.2.1. Profitability, and especially firm listing age, accounts for a substantial portion of the variation in *KZ* that a more parsimonious specification would otherwise attribute to fin-tech development.

4.2 Baseline Results

Table 2. Fin-tech Development and Financing Constraints: Firm FE (Preferred)

	(1)
	KZ
lnFintech	-0.693^{**}
	(0.340)
size	-0.246^{***}

	(0.046)
roa	-5.817***
	(0.242)
tang	2.950***
	(0.161)
top1	-0.009***
	(0.003)
lnage	1.434***
	(0.061)
tagr	-1.059***
	(0.048)
lnFir	-0.079
	(0.122)
_cons	6.534***
	(2.168)
Observations	23002.000
Adj. R-squared	0.638

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In our preferred specification with firm and year fixed effects, the coefficient on *lnFintech* is negative and significant at the 5% level (β = −0.693). The estimate remains unchanged when standard errors are clustered at the city level, while the standard error falls to 0.324. Clustering at this level is relevant because *lnFintech* varies across cities (Cameron and Miller, 2015).

A one-standard-deviation increase in *lnFintech*, approximately 0.42, is associated with a 0.29-point decline in the KZ index, equivalent to about 0.14 standard deviations of KZ. Although modest, this effect is economically meaningful because firm fixed effects identify the relationship from changes within firms over time rather than from the cross-sectional differences available to a coarser specification.

4.2.1 Robustness to an Alternative Fixed-Effects Structure

Table 3. Fin-tech Development and Financing Constraints: Industry FE (Robustness)

	(1)	(2)
	KZ	KZ
lnFintech	-1.500***	-0.212
	(0.243)	(0.245)

size		-0.024
		(0.020)
roa		-10.213***
		(0.271)
tang		1.419***
		(0.126)
top1		-0.006***
		(0.001)
lnage		0.604***
		(0.030)
tagr		-1.025***
		(0.053)
lnFir		-0.052
		(0.062)
_cons	8.956***	1.485
	(1.290)	(1.361)
Observations	23556.000	23096.000
Adj. R-squared	0.117	0.398

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As a further robustness comparison, we re-estimate the baseline model using industry and year fixed effects instead of firm fixed effects, a coarser structure commonly used in the related literature. Without additional controls, the coefficient *on lnFintech* is negative and significant at the 1% level ($\beta = -1.500$). Once the full set of firm-level controls is included, the coefficient falls to −0.212 and is no longer statistically significant. By comparison, the firm fixed effects estimate remains significant with the same controls.

Table 4. Diagnostic: *lnFintech* Coefficient as Controls Are Added Sequentially

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	No control	+size	+roa	+tang	+top1	+lnage	+tagr	+lnFir
lnFintech	-1.500***	-1.505***	-0.861***	-0.493**	-0.425**	0.027	-0.054	-0.212
	(0.243)	(0.243)	(0.196)	(0.197)	(0.198)	(0.185)	(0.185)	(0.245)
Observations	23556.000	23556.000	23556.000	23158.000	23142.000	23142.000	23141.000	23096.000
Adj. R-squared	0.117	0.117	0.297	0.315	0.319	0.373	0.397	0.398

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To explain this contrast, we re-estimate the model with industry fixed effects and add the seven controls sequentially in the order shown in Table 4. Two changes stand out. First, adding *roa* in column (3) reduces the coefficient on *lnFintech* from −1.505 to −0.861, a decline of about 43%. This change is consistent with the raw correlation of −0.45 between *roa* and *KZ* reported in Section 4.1. It also reflects the close relationship between accounting profitability and the operating cash flow component of the KZ index.

The second important change occurs when listing age is added. The coefficient on *lnFintech* moves from −0.425 in column (5), where it remains significant, to 0.027 in column (6), where it is no longer significant. Listing age is strongly associated with *KZ* throughout, with coefficients ranging from 0.60 to 0.69. Since higher *KZ* values indicate tighter financing constraints, the positive coefficient implies that longer-listed firms have higher *KZ* values in this sample. This result runs counter to the expectation that a longer track record and broader analyst coverage should ease access to external finance, so the coefficient requires cautious interpretation.

One possible explanation for the movement in the *lnFintech* coefficient is collinearity between *lnFintech* and *lnage*. Their raw correlation is 0.066. After removing the effects of size, *roa*, *tang*, *top1*, and industry-by-year fixed effects from both variables, the partial correlation is −0.096. Its absolute value is slightly larger than the raw correlation, but both remain modest. Neither approaches the levels commonly associated with serious collinearity, such as partial correlations above 0.5 to 0.7 or variance inflation factors above 5 to 10. Severe collinearity is therefore unlikely to explain the coefficient movement. The results are more consistent with omitted variable bias in the less complete specification, where *lnFintech* absorbs some of the variation associated with listing age when *lnage* is excluded.

This comparison also explains why the specification with firm fixed effects remains our preferred model. Together with the observed controls, firm fixed effects nonparametrically account for all time-invariant differences across firms, including unobserved factors that industry fixed effects cannot capture. The result reported in Section 4.2 remains the main finding for H1, while the analysis in this subsection serves as a robustness comparison.

4.3 Mechanism Analysis

All mechanism tests in this section use the preferred firm and year fixed-effects specification established in Section 4.2.

Debt cost channel (H3).

Table 5. Mechanism Test: Debt Cost (H3)

	(1)	(2)
	DebtCost	KZ
lnFintech	-0.029***	-0.494
	(0.008)	(0.329)
size	0.004***	-0.277***
	(0.001)	(0.045)
roa	-0.049***	-5.492***
	(0.005)	(0.237)
tang	0.055***	2.541***
	(0.004)	(0.161)
top1	-0.000***	-0.009***
	(0.000)	(0.003)
lnage	0.017***	1.143***
	(0.001)	(0.061)
tagr	0.005***	-1.071***
	(0.001)	(0.048)
lnFir	-0.005*	-0.052
	(0.003)	(0.117)
DebtCost		7.921***
		(0.464)
_cons	0.018	6.907***
	(0.045)	(2.114)
Observations	25096.000	22997.000
Adj. R-squared	0.557	0.648

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the first stage of the mediation analysis, fin-tech development is negatively associated with firms' cost of debt (β =-0.029). This result is consistent with the mechanism developed in Section 2.3. More developed digital financial infrastructure may give lenders access to richer borrower information, including transaction histories, supply-chain data, and machine-learning risk models. Better information can improve credit-risk assessment and allow lenders to price loans more accurately, potentially lowering financing costs for otherwise comparable borrowers.

In the second stage, *DebtCost* enters the financing-constraint equation with a positive and statistically significant coefficient (β =7.921). Firms with higher debt costs therefore tend to face tighter financing constraints. After *DebtCost* and the full set of controls are included, the coefficient on *lnFintech* declines from -0.693 to -0.494 and is no longer statistically significant.

This combination of results is consistent with full, or indirect-only, mediation. The total effect reported in Table 2 is significant, both paths forming the indirect effect are significant, and the remaining direct effect is statistically indistinguishable from zero after the mediator is included. The pattern satisfies the classical Baron and Kenny criteria and is also consistent with the bootstrap-based framework of Zhao, Lynch, and Chen (2010).

The cluster-bootstrap estimates provide direct evidence for the indirect path. Based on 2,000 replications resampled at the firm level, the estimated indirect effect is -0.228, with a bootstrap standard error of 0.065. The 95 percent percentile confidence interval ranges from -0.356 to -0.097 and excludes zero. The indirect effect also appears to be estimated more precisely than in the industry fixed-effects diagnostic reported in Section 4.2.1.

Taken together, the estimates support H3 and identify debt cost as an important channel linking fin-tech development to financing constraints. In this sample, the results are consistent with the relationship operating largely, and possibly entirely, through the price of credit. Because the direct effect is estimated imprecisely rather than proven to be exactly zero, the evidence does not rule out smaller additional channels.

Bank competition channel (H2).

Table 6. Mechanism Test: Bank Competition (H2)

	(1)	(2)
	bankcomp	KZ
lnFintech	-0.008***	-0.666**
	(0.002)	(0.339)
size	0.000	-0.246***
	(0.000)	(0.046)
roa	-0.001	-5.814***
	(0.001)	(0.242)

tang	-0.000	2.951***
	(0.001)	(0.161)
top1	0.000*	-0.009***
	(0.000)	(0.003)
lnage	-0.000	1.433***
	(0.000)	(0.061)
tagr	0.000*	-1.059***
	(0.000)	(0.048)
lnFir	0.005***	-0.098
	(0.001)	(0.122)
bankcomp		3.471
		(2.868)
_cons	0.958***	3.216
	(0.012)	(3.437)
Observations	25101.000	23002.000
Adj. R-squared	0.981	0.638

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The first-stage estimate for the bank-competition channel changes when firm fixed effects replace industry fixed effects. Within firms, fin-tech development is associated with a small but statistically significant decline in the branch-based competition measure (β =-0.008). This sign contrasts with both the raw cross-sectional correlation of 0.361 and the positive relationship estimated under industry fixed effects.

The reversal should be interpreted cautiously. Our competition measure is based on the physical distribution of bank branches and does not capture competition through digital channels. Incumbent banks may respond to fin-tech development by expanding their online capacity while consolidating branch networks. If so, greater fin-tech intensity could coincide with lower measured branch competition even as competition across both physical and digital channels increases. This remains a possible measurement explanation rather than a result directly established by our data. Section 5 discusses the limitation further.

The magnitude of the estimated coefficient is also small. In addition, the first-stage model has an adjusted R^2 of 0.981. The mediator varies little within firms because it is measured for each firm's home city, which typically does not change during the sample period. The first-stage estimate should therefore be treated with some caution because the coefficient is small and *bankcomp* varies little within firms.

The second link in the mediation chain is clearer. Bank competition is not significantly associated with financing constraints (β =3.471). The cluster-bootstrap estimate of the indirect effect is likewise insignificant. The estimated effect is -0.028, with a bootstrap standard error of 0.024. Its 95 percent percentile confidence interval ranges from -0.081 to 0.016 and includes zero.

The industry and firm fixed-effects specifications therefore lead to the same conclusion about H2: neither provides statistically significant evidence that bank competition mediates the relationship between fin-tech development and corporate financing constraints. In contrast, the debt-cost results consistently support H3. For the listed firms in our sample, the evidence points to the price of credit rather than branch-based local bank competition as the more relevant channel.

4.4 Robustness Checks

Table 7. Robustness Checks

	(1)	(2)	(3)	(4)	(5)
	Baseline	SA Index	Alt.Fintech proxy	Excl.Finance/Real Estate	Excl.ST Firms
lnFintech	-0.693**	-0.021		-0.866**	-0.803**
	(0.340)	(0.025)		(0.342)	(0.345)
size	-0.246***		-0.244***	-0.292***	-0.239***
	(0.046)		(0.046)	(0.049)	(0.047)
roa	-5.817***	-0.058***	-5.828***	-5.694***	-5.855***
	(0.242)	(0.022)	(0.242)	(0.245)	(0.250)
tang	2.950***	-0.033***	2.946***	2.828***	2.986***
	(0.161)	(0.013)	(0.161)	(0.173)	(0.165)
top1	-0.009***	0.000	-0.009***	-0.011***	-0.010***
	(0.003)	(0.000)	(0.003)	(0.003)	(0.003)
lnage	1.434***		1.439***	1.431***	1.431***
	(0.061)		(0.061)	(0.063)	(0.062)
tagr	-1.059***	-0.001	-1.059***	-1.114***	-1.055***
	(0.048)	(0.002)	(0.048)	(0.047)	(0.048)
lnFir	-0.079	-0.004	-0.072	-0.063	-0.097
	(0.122)	(0.010)	(0.122)	(0.123)	(0.125)
lnFintech_alt			0.037		
			(0.036)		
_cons	6.534***	-3.741***	2.682***	8.577***	6.976***
	(2.168)	(0.131)	(1.015)	(2.183)	(2.212)
Observations	23002.000	25393.000	23002.000	21673.000	22431.000
Adj. R-squared	0.638	0.936	0.638	0.637	0.636

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7 reports four robustness tests based on the preferred specification with firm and year fixed effects, *lnFir*, and the remaining controls. Each test addresses a different potential source of sensitivity.

Sample composition. We first exclude firms in the financial and real estate industries. The coefficient on *lnFintech* remains negative and statistically significant and is larger in magnitude than the full-sample estimate (β =-0.866, compared with -0.693 in the baseline). These industries therefore do not appear to drive the main result.

We then exclude ST and *ST firms. The estimated coefficient remains negative, statistically significant, and similar in magnitude to the baseline (β =-0.803). The result is thus not concentrated among financially distressed firms.

Alternative independent variable. Replacing the PKU index with the registration-count-based proxy, *lnFintech_alt*, produces a small positive coefficient that is not statistically significant (β =0.037). Under the earlier industry fixed-effects specification, this proxy produced a statistically significant coefficient with the opposite sign. That sign reversal is no longer statistically distinguishable from zero under firm fixed effects.

The two proxies still do not yield the same estimate. We continue to prefer the PKU index for the construct-validity reasons discussed in Section 3.2, particularly because it is intended to measure realized fin-tech penetration rather than company registrations. The weaker discrepancy under the preferred specification reduces, but does not eliminate, the concern raised by the alternative measure.

Alternative dependent variable. When the SA index replaces KZ, the coefficient on *lnFintech* is negative but not statistically significant (β =-0.021). Firm size and age are excluded from the control set in this model because they are deterministic components of the SA index.

The SA index is a slow-moving function of firm size and age, both of which change gradually within a firm over the ten-year sample period. Firm fixed effects remove the between-firm variation that ordinarily contributes to identification, leaving comparatively little within-firm movement in SA. Consistent with this limitation, the model has a within R^2 of 0.0047, compared with 0.29 to 0.33 in the other firm fixed-effects specifications. This feature may explain the imprecise estimate, but the result should still be reported as a limitation rather than treated as confirmation of the baseline finding.

Taken together, the sample-exclusion tests support the baseline result. The alternative fin-tech proxy produces a smaller and statistically insignificant discrepancy under firm fixed effects, although the two measures remain imperfectly aligned. The SA specification is less informative because the dependent variable contains limited within-firm variation, but it also shows that the main conclusion is not equally strong across all measures of financing constraints.

5. Conclusion

This paper examines whether fin-tech development eases corporate financing constraints and through which channels. We combine a panel of Chinese A-share listed firms with city-level measures of fin-tech development, bank competition, and regional financial development. In our preferred specification with firm and year fixed effects, fin-tech development is significantly associated with lower financing constraints. The finding remains significant when standard errors are clustered at the city level.

We also compare the preferred model with a coarser specification that includes industry and year fixed effects. Under that alternative structure, the estimated coefficient weakens after firm characteristics are introduced. The sequential diagnostic identifies firm listing age as an important source of this attenuation. This comparison helps explain why firm fixed effects, together with the observed controls, provide more complete control for heterogeneity across firms.

The mechanism analysis points to debt cost as the main channel. Fin-tech development significantly lowers firms' cost of debt, and lower debt costs significantly ease financing constraints. Once debt cost is included, the direct effect of fin-tech is no longer statistically significant. This pattern is consistent with indirect-only, or full, mediation under both classical and modern criteria. Fin-tech development is also associated with local bank competition, although the sign of this relationship varies across specifications. More importantly, bank competition does not significantly ease financing constraints under either fixed effects structure.

The findings have two policy implications. First, measures that improve the pricing of credit may be more useful for listed firms than policies focused only on increasing the number of lenders in a market. Encouraging lenders to adopt big-data credit assessment, for example, may help them evaluate borrower risk more accurately and set lending rates accordingly. Second, the insignificant bank competition channel should not be generalized beyond the listed firms in our sample. Smaller, more credit-rationed unlisted firms may respond differently to changes in local banking competition. Examining this possibility requires firm-level data with broader coverage of small and medium-sized enterprises.

The study also has several limitations. First, identification relies on fixed effects rather than a fully exogenous source of variation in fin-tech development. Although the results remain stable across several specifications and clustering levels, residual endogeneity cannot be ruled out. Future studies could use exogenous policy changes, such as staggered introductions of regional fin-tech regulatory pilots.

Second, debt cost is measured as financial expenses divided by total liabilities. Because total liabilities include non-interest-bearing obligations, this ratio may understate the cost associated specifically with interest-bearing debt. Where the necessary data are available, a measure based only on interest-bearing debt would provide a more precise estimate of this channel.

Third, the bank competition measure is based on the physical distribution of bank branches within prefecture-level cities. The relationship between fin-tech and this measure changes sign between the raw cross-sectional data and the estimates based on changes within firms. One possible explanation is that branch-based indices do not fully capture competition through digital channels. Banks may expand online services while reducing their physical branch networks, causing measured branch competition to decline even if broader competitive pressure increases. The data do not test this explanation directly, but the sign reversal shows that physical branch coverage is an imperfect measure of competition in a more digital banking system. It may also help explain why the bank competition channel is insignificant even though the theoretical mechanism in Section 2.2 remains plausible.

Fourth, combining firm fixed effects with the SA index removes much of the variation available for identification. The insignificant coefficient in this specification should therefore be interpreted cautiously rather than as evidence against the main result. Researchers using the SA index as their primary measure may prefer industry or regional fixed effects, which preserve more of its largely cross-sectional variation. Future research could combine exogenous policy shocks with survey data on firms' realized borrowing costs. Measures of bank competition that include digital channels would help assess whether branch-based indices understate changes in competitive intensity. Broader samples that include unlisted small and medium-sized enterprises would also show whether the mechanisms identified here extend beyond publicly listed firms.

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