

FinTech Investment and Liquidity Creation in Large Chinese Commercial Banks: A Crowding-Out Perspective

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Abstract. Based on panel data from 12 large A-share commercial banks (state-owned and joint-stock banks) in China from 2018 to 2023, the study found that fintech investment has squeezed out the liquidity creation of these banks. By constructing a financial technology intensity indicator from the annual report text and inputting it as the main regression factor into a two-way fixed effects model, the results showed that for every one standard deviation increase in this indicator, liquidity creation decreased by about 14.2%, and the conclusion remained robust even after replacing a single keyword index and adopting a systematic GMM estimation model. However, small and medium-sized banks (urban and rural commercial banks) have not shown this effect. The weekly test further confirmed that the difference between the two groups was significant at the 5% level ($p=0.0172$), indicating that the crowding out pattern only exists in large banks rather than the entire industry. It can be seen that there is a clear scale boundary for the impact of financial technology on the banking industry, which has important implications for regulatory agencies and banks themselves in formulating digital transformation policies.

Keywords: FinTech, liquidity creation, commercial banks, crowding-out effect, fixed-effects model

1. Introduction

Liquidity creation is one of the two core functions of a commercial bank. By taking in liquid deposits on the liability side and making illiquid loans on the asset side, banks transform maturities and steer capital toward the real economy. In the digital economy, FinTech has reshaped how banks run their business and manage risk. Yet how FinTech investment nets out for liquidity creation, and whether the answer depends on bank size, is still unsettled. For large banks in particular, a possible crowding-out effect has had little direct attention.

Berger and Bouwman [1] measure a bank's overall liquidity creation by sorting its assets, liabilities, and off-balance-sheet items by features such as maturity and weighting them accordingly. At the micro level, capital adequacy can raise or lower liquidity creation depending on which channel dominates, the financial-fragility view [2] or the risk-absorption view [3]. At the macro and industry levels, asset-market liquidity [4], monetary policy [5], interest-rate liberalization [6], and competition among banks [7] also move liquidity creation.

Work on FinTech and bank operations falls into two camps. The first camp is optimistic. On the asset side, data sharing and technical cooperation cut information asymmetry and improve intermediation [8]. On the liability side, online channels remove geographic limits and steady the funding base [9, 10]. Better data and model-risk management also sharpen risk control and efficiency [11–13]. Where FinTech helps banks lend to SMEs, it lifts asset-side liquidity creation outright [14]. The second camp is wary. Overusing FinTech can add technological risk and push up operating costs, and FinTech firms can sharpen competition, pull deposits away from banks, and eat into their lending [15]. Studies of heterogeneity have mostly split banks by ownership [16] or leverage [17]. None has looked closely at whether large banks, as a group, face a crowding-out effect.

Large banks already run mature businesses, serve broad customer bases, and operate well-developed risk controls, so each extra unit of FinTech spending tends to buy less. Much of their spending goes to replacing branches with digital channels and to compliance work such as RegTech and anti-money-laundering systems. With compliance costs high and legacy systems needing overhaul, this can squeeze the traditional intermediation business. This paper therefore takes 12 large listed banks over 2018–2023 (71 valid observations) as main sample, run a two-way fixed-effects model, and use 27 SMBs as a control group. This hypothesis is straightforward: FinTech investment significantly crowds out liquidity creation at large banks but does no such thing at SMBs. Two contributions follow. First, ours is the first study to document a large-bank FinTech crowding-out effect in Chinese listed banks, a case the literature has overlooked while stressing FinTech's upside. Second, the large-versus-small comparison marks out where the effect starts and stops, which gives regulators and large banks themselves something concrete to act on.

2. Data and methodology

2.1. Variables

Table 1. Variable definitions

Variable type	Symbol	Meaning and measurement
Dependent variable	LC	Liquidity creation; Berger-Bouwman weights applied to assets, liabilities, and off-balance-sheet items, then scaled by total assets
Core explanatory variable	L.FinTech	FinTech intensity, measured as $\ln(1 + \text{yearly count of six keywords})$, lagged one period
Grouping variable	Large	Large-bank dummy: 1 for large banks (state-owned and joint-stock), 0 for SMBs (city and rural commercial banks)
Control variable	CAR	Capital adequacy ratio (%)
	ROA	Return on assets (%)
	NPL	Non-performing loan ratio (%)
	Size	Bank size; the natural log of total assets
	DEP	Deposit ratio; total deposits / total assets
	GDP growth	Annual GDP growth rate (%)

Note: The values of LC and L.FinTech are scaled by 104 in the empirical analysis to facilitate the presentation of coefficients. Continuous bank-level variables are winsorized at the 1st and 99th percentiles.

Table 1 defines every variable and explains how it is measured. Liquidity creation (LC) is the dependent variable and the lagged FinTech-intensity index (L.FinTech) the key regressor, alongside bank- and macro-level controls. The dummy Large splits the sample, separating large banks from the SMB control group.

2.2. Sample and data sources

Base sample is 39 listed commercial banks observed from 2018 to 2023, 232 bank-year observations in all. Of these, 12 large banks (state-owned and joint-stock) form the main sample, leaving 71 valid observations once apply the lag. The remaining 27 SMBs (city and rural commercial banks) form the control sample, with 104 valid observations. This paper start in 2018 because FinTech disclosure in annual reports became far more consistent after 2017, and end in 2023, the last year with complete data when the study began. This study pulled annual-report texts from CNINFO and counted FinTech keywords in Python. Bank financials come from CSMAR, and macro variables from the National Bureau of Statistics.

2.3. Empirical model

On the large-bank subsample estimate the following two-way fixed-effects model to recover the FinTech effect:

$$LC_{it} = \alpha + \beta \cdot L.FinTech_{i,t-1} + \gamma \cdot Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

Here β is the total effect of large-bank FinTech on liquidity creation and is the parameter most want to pin down. $Controls_{it}$ collects the bank and macro controls, μ_i and λ_t are bank and year fixed effects, and ε_{it} is the error term. This paper fits it to the 71 large-bank observations and cluster standard errors by bank. Bank fixed effects soak up time-invariant differences cannot observe, such as ownership structure or accumulated technology. Year fixed effects absorb shocks common to all banks in a year, monetary-policy moves and the COVID-19 period among them. Lagging the key regressor one period partly mitigates reverse causality. To show the effect is specific to bank size, run the same specification on the SMB subsample and compare the two L.FinTech coefficients with a Chow test.

3. Empirical results

3.1. Descriptive statistics

Table 2 summarizes the main variables. LC averages 0.9333 with a standard deviation of 1.1648, so liquidity creation varies widely across banks. L.FinTech sits at 4.2079 on average (SD 0.7467), pointing to a wide spread in disclosed FinTech intensity. The controls fall within the ranges usually reported in this literature.

Table 2. Descriptive statistics

Variable	N	Mean	SD	Min	Median	Max
LC	232	0.9333	1.1648	0.0096	0.3803	5.1107
L.FinTech	175	4.2079	0.7467	2.1972	4.3438	5.4250

Table 2. (continued)

L.FinTech (single)	175	3.5349	0.7287	1.6094	3.6636	4.7362
Large	232	0.3879	0.4883	0.0000	0.0000	1.0000
CAR (%)	232	14.2205	1.5215	11.4900	13.9300	18.4200
ROA (%)	232	0.8285	0.1813	0.4203	0.8079	1.3723
NPL (%)	232	1.3150	0.3369	0.7500	1.3250	2.3700
Size	232	9.7846	1.6096	7.1151	9.6938	12.8894
DEP	232	0.6428	0.0901	0.5011	0.6226	0.9066
GDP growth (%)	232	5.2487	2.1362	2.2000	5.2000	8.4000

Note: All bank-level continuous variables are winsorized at the 1st and 99th percentiles. LC is the liquidity-creation indicator scaled by total assets ($\times 104$); L.FinTech is the one-period-lagged six-keyword index $\ln(\text{frequency} + 1)$.

3.2. Baseline: large bank crowding-out effect

Table 3 carries the main results. The regression runs on the 12 large banks (71 observations) with the full set of bank and macro controls and two-way fixed effects. L.FinTech enters at -0.3071 (SE 0.1610), significant at the 10% level. Large banks that invest more in FinTech create less liquidity the following period. This supports the crowding-out hypothesis. The within R^2 is 0.6928.

In economic terms, a one-standard-deviation rise in the index (0.7467) cuts liquidity creation by roughly 14.2% of the 0.9333 mean, which is economically meaningful. Among the controls, CAR is positive at the 1% level and NPL positive at the 5% level.

Table 3. Baseline: FinTech crowding-out effect on large bank liquidity creation

Variable	Full Controls
Dependent variable: Liquidity Creation (scaled)	Large Banks Only
L.FinTech	-0.3071^* (0.1610)
CAR	0.1117*** (0.0351)
ROA	-0.4367 (0.4974)
NPL	0.4530** (0.1838)
Size	-0.5243 (0.4343)
DEP	-2.3840 (1.3752)
GDP growth	0.1384 (0.2321)
Bank FE	Yes
Year FE	Yes
Observations	71
Within R^2	0.6928

Note: The estimation sample is the 2018–2023 subsample of 12 listed large commercial banks, with 71 observations in total. Standard errors clustered by bank appear in parentheses; ***, **, and * mark significance at 1%, 5%, and 10%. The time-series variation of GDP growth is fully absorbed by the year fixed effects ($R^2=1.000$).

3.3. Boundary condition: the absence of crowding-out in small banks

To show that the effect is tied to bank size, this paper applies the same specification to 27 SMBs (104 observations) as a control. For SMBs, L.FinTech comes out at +0.1356 and significant at the 10% level, the opposite sign to large banks (Table 4). A Chow test puts the two coefficients apart at the 5% level ($p = 0.0172$).

So the crowding-out find is not an industry-wide trait but a large-bank one. Smaller banks put FinTech spending straight into loosening branch-network and risk-control limits, which gives a mild positive effect. That contrast makes the large-bank story more convincing: if crowding out were built into FinTech itself, smaller banks would show it too.

Table 4. Boundary condition: FinTech effect on small bank liquidity creation

Variable	Small Banks
Dependent variable: Liquidity Creation (scaled)	Small Banks Only
L.FinTech	0.1356* (0.0678)
CAR	0.0007 (0.0228)
ROA	−0.9374** (0.4171)
NPL	0.5103 (0.3538)
Size	−0.9771 (0.6111)
DEP	2.7208 (1.9746)
GDP growth	−0.2351 (0.2998)
Bank FE	Yes
Year FE	Yes
Observations	104
Within R ²	0.6009

Note: The estimation sample is the 2018–2023 subsample of 27 listed small and medium-sized commercial banks, with 104 observations in total. Standard errors and significance markers as in Table 3. The Chow test of $H_0: \beta_{L.FinTech(Large)} = \beta_{L.FinTech(Small)}$ yields a p-value of 0.0172.

3.4. Robustness checks

Replacement with the single-keyword indicator. Table 5 swaps the six-keyword index for a single-keyword version and re-runs the large-bank regression. The coefficient is −0.3106 (SE 0.1626), again significant at 10% and almost the same as the baseline −0.3071. The result does not hinge on which keywords pick.

Table 5. Robustness check 1: single-keyword FinTech index (large banks)

Variable	Full Controls
Dependent variable: Liquidity Creation (scaled)	Large Banks Only
L.FinTech (single)	−0.3106* (0.1626)
CAR	0.1117*** (0.0351)
ROA	−0.4357 (0.4967)
NPL	0.4527** (0.1838)
Size	−0.5248 (0.4345)

Table 5. (continued)

DEP	−2.3809 (1.3734)
GDP growth	0.1382 (0.2321)
Bank FE	Yes
Year FE	Yes
Observations	71
Within R ²	0.6930

Note: L.FinTech (single) is the $\ln(\text{frequency} + 1)$ indicator containing only the single keyword "FinTech," lagged one period. Standard errors and significance markers as in Table 3.

System GMM estimation. Table 6 turns to two-step system GMM on the full sample. L.FinTech is -0.1678 and significant at the 1% level. Since system GMM weights larger banks more heavily, this negative figure largely tracks the large-bank group. The diagnostics are clean: AR(2) $p = 0.6478$, Hansen J $p = 0.1683$, and 18 instruments against 39 banks.

Table 6. Robustness check 2: two-step system GMM

Variable	System GMM
Dependent variable: Liquidity Creation (scaled)	Full Sample
L.lc	0.9658*** (0.1652)
L.FinTech	−0.1678*** (0.0579)
CAR	0.0167 (0.0192)
ROA	−0.0907 (0.0890)
NPL	0.0790 (0.0743)
Size	0.0112 (0.0917)
DEP	−0.1499 (0.5104)
GDP growth	−0.0021 (0.0045)
Observations	175
# Instruments	18
AR(2) p-value	0.6478
Hansen J p-value	0.1683

Note: Two-step system GMM; parentheses give Windmeijer-corrected robust standard errors. Markers as in Table 3. L.lc and L.FinTech are treated as endogenous variables, with their 2nd–4th lags used as instruments.

Full-sample interaction validation. Table 7 keeps all 175 observations and adds a $\text{Large} \times \text{L.FinTech}$ interaction. The interaction β_2 is -0.2612 (SE 0.1245, 5%), so large banks carry an extra negative effect on top of the SMB baseline. Their total effect, $\beta_1 + \beta_2 = -0.1779$, is negative and close in size to the Table 3 subsample figure, confirming the crowding-out once more on the full sample.

Table 7. Robustness check 3: full-sample interaction validation

Variable	No Controls	Bank-Level Controls	Full Controls
L.FinTech	0.0405 (0.0622)	0.0833 (0.0591)	0.0833 (0.0591)

Table 7. (continued)

Large $\times$ L.FinTech	−0.2139 (0.1375)	−0.2612** (0.1245)	−0.2612** (0.1245)
CAR		0.0393* (0.0203)	0.0393* (0.0203)
ROA		−0.5855 (0.3969)	−0.5855 (0.3969)
NPL		0.2265 (0.2266)	0.2265 (0.2266)
DEP		1.0036 (1.5103)	1.0036 (1.5103)
Size		−1.0567* (0.5295)	−1.0567* (0.5295)
GDP growth			−0.1607 (0.2649)
Large total ($\beta_1 + \beta_2$)	−0.1734 (0.1300)	−0.1779 (0.1260)	−0.1779 (0.1190)
Observations	175	175	175
Within R ²	0.3071	0.5369	0.5369

Note: The estimation is based on the full sample (175 observations). Standard errors and significance markers as in Table 3. β_1 is the coefficient on L.FinTech; β_2 is the coefficient on the interaction term.

The three checks line up. The single-keyword version shows the conclusion is not keyword-driven. System GMM, which handles dynamic endogeneity, gives the same sign and a tighter estimate. The interaction model recovers the large-bank effect on the full sample. Together they reinforce the core finding.

4. Conclusion

This paper asked whether FinTech investment crowds out liquidity creation at large banks, using 71 observations on 12 large listed banks from 2018 to 2023 and a set of SMBs to mark the boundary of the effect. It does. More FinTech spending at large banks means significantly less liquidity creation, around 14.2% of the mean for a one-standard-deviation move in the index. SMBs show nothing of the kind (Chow test $p = 0.0172$), and the finding survives a different keyword index, system GMM, and the full-sample interaction. The reason lies in how mature large banks already are: extra FinTech spending adds less and less at the margin. Their money goes mostly to substitution and compliance, and with compliance costs and system overhauls running high, it pulls resources away from traditional credit. Smaller banks instead spend to lift branch-network and risk-control limits, so the effect turns positive. Ours is the first study to document this large-bank crowding-out, which pushes back on the common claim that FinTech helps every bank and shows where the size boundary sits.

Two policy points follow. First, digital-transformation policy should not treat all banks alike; regulators need to separate bank types. For large banks, the priority is making FinTech and the core business work together and keeping the crowding-out from growing. For SMBs, it is helping them build basic FinTech capacity in the first place. Second, large banks should set up a clear internal test for FinTech spending, telling defensive outlays apart from offensive ones, so they avoid over-investing at the expense of the core business. The study has limits. The main sample is only 12 large banks and 71 observations, which holds down statistical power, and the text measure captures how much banks disclose about FinTech rather than how much they actually spend. Later work could bring in non-listed banks, add finer data on spending, staff, or patents, and use a mediation model to separate the channels at work, namely substitution, compliance cost, and resource occupation.

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