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Internal regulatory technology (RegTech) and bank liquidity risk: evidence from Chinese listed banks

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ABSTRACT
We examine the effect of internal regulatory technology (RegTech) on bank liquidity risk. Based on a dataset of Chinese listed banks from 2015 to 2022, we initially employ a text-mining method to build the internal RegTech index from the banks' annual reports. We subsequently reveal a significant mitigation effect of internal RegTech on bank liquidity risk. The finding remains robust after alleviating the endogeneity issue and under alternative proxy of the dependent variable and different sample periods. A possible channel is that internal RegTech boosts the regulatory capability and mitigates banks' risky behaviours. Moreover, our results demonstrate some heterogeneities across RegTech subindices. The compliance and technological foundations subindices are more profound in affecting bank liquidity risk. The findings provide valuable implications for financial regulators regarding the adoption of RegTech.

KEYWORDS
Regulatory technology; bank; liquidity risk; text-mining

JEL CLASSIFICATION
G21; G28; O14

I. Introduction

Bank liquidity risk refers to a bank's inability to meet its payment obligations as liabilities fall due. The traditional banking theory highlights that maturity transformation enhances banks' profitability but exposes banks to a threat of liquidity risk and bank runs. The downfall of Silicon Valley Bank shocked the global financial system, and one of the major reasons was poor liquidity management. Current research highlights the determinants of liquidity risk, including bank-level factors (Abdul-Rahman, Sulaiman, and Mohd Said 2018) and monetary policy (Nguyen, Nguyen, and Duong 2023). Moreover, financial regulation is a direct solution to bank liquidity risk (Raz, McGowan, and Zhao 2022).

The stringent regulatory standards and traditional regulatory models have posed numerous compliance costs to banks and have long been debated because of regulatory lag and inconsistency, which spur the emergence of regulatory technology (RegTech). RegTech described technology usage in regulation, monitoring, reporting, and compliance (Buckley et al. 2020). The definition falls into the internal RegTech powered by the regulated entities to enhance compliance effectiveness (Teichmann, Boticiu, and Sergi 2023) and improve risk management (Chao et al. 2022).

RegTech can also be driven by regulatory authorities, referred to as external RegTech, which implies adopting technology in financial regulation for higher regulatory efficiency and capability. There is a potential interaction between internal and external RegTech. Theoretically, internal RegTech can mitigate liquidity risk in two ways. Monitoring and Know-Your-Customer systems can directly identify and provide an early warning of potential risks. Indirectly, the internal RegTech establishes an efficient information and reporting system, which boosts automatic and timely regulation. However, there is a noticeable research gap regarding the role of internal RegTech on bank liquidity risk. This paper, therefore, aims to bridge the knowledge gap.

The marginal contribution of this paper is threefold. First, we enter into the debate on the nexus between financial regulation and bank liquidity risk and provide solid evidence on the risk-mitigation effect of internal RegTech. Second, we are the first to measure the bank-level RegTech and empirically explore the nexus. The empirical results can

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supplement the abundant theoretical analysis of RegTech on risk management (Buckley et al. 2020; Chao et al. 2022). Finally, we perform a mechanism analysis of how internal RegTech affects bank liquidity risk.

II. Data and variables

Sample

We selected all 41 commercial banks listed in the Chinese A-share market from 2015 to 2022 as the sample. These banks accounted for approximately 84% of the total assets of the whole Chinese banking industry in 2022. The dataset was collected from the CSMAR database, the commercial banks' annual report, and the State Administration for Financial Regulation website.

Variables

Dependent variable

We follow Ghenimi, Chaibi, and Omri (2017) to employ the liquidity ratio (*LDR*) as a proxy of bank liquidity risk, which is computed as:

$$LDR = \frac{LA}{LL} \times 100\%, \tag{1}$$

where *LA* and *LL* denote the liquid assets and liquid liabilities, respectively. We take the natural logarithm of the *LDR* (*LnLDR*).

Core explanatory variable

The internal RegTech index is utilized to measure the application of RegTech in banks. We employ a text-mining method to build the internal RegTech index from the banks' annual reports. Briefly speaking, we select a series of RegTech-related keywords and count the word frequency of these keywords. The natural logarithm of the frequency is employed as a proxy of the internal RegTech (*LnRegTech*) (see details in Appendix A).

Control variables

We follow Abdul-Rahman, Sulaiman, and Mohd Said (2018) and Raz, McGowan, and Zhao (2022) to employ return on assets (*ROA*), bank size (*SIZE*), capital adequacy ratio (*CAR*), net interest margin (*NIM*), non-interest income ratio (*NIIR*), net profit margin on income (*NPGOI*), administrative expenses on income (*AEGOI*), and total assets turnover (*TAT*). The summary statistics and definitions are displayed in Table 1.

Econometric model

To examine the impact of internal RegTech on bank liquidity risk, we construct the following two-way fixed-effect model:

$$LnLDR_{i,t} = \alpha_0 + \alpha_1 lnregtech_{i,t} + \alpha_2 Control_{i,t} + \delta_i + \mu_t + \varepsilon_{i,t}, \tag{2}$$

where i and t denote the i-th bank and the t-th year, respectively. The *Control* indicates the control variables. δ and μ imply the bank and year fixed effects, respectively. ε is the error term.

Table 1. Summary statistics.

Variable	Obs	Mean	SD	Min	Max	Definition
LnLDR	326	4.737	0.928	1.386	5.720	$\ln\left(100 \times \frac{\text{Liquid assets}}{\text{Liquid liabilities}}\right)$
LnRegTech	326	5.383	0.709	2.890	7.069	The natural logarithm of word frequency of the internal RegTech-related keywords
ROA	326	0.008	0.002	0.004	0.016	Net profit/Total assets
Size	326	1.443	0.026	1.401	1.494	Natural logarithm of total assets (in hundred billion)
CAR	326	13.789	1.582	10.940	18.420	Capital/Risk-weighted assets
NIM	326	2.226	0.401	1.520	3.460	100 × Net interest income/Interest-earning assets
NIIR	326	21.122	10.201	0.679	44.233	100 × Non-interest income/Net income from operations
NPGOI	326	32.637	6.306	14.771	44.570	100 × Net profit/Revenue
AEGOI	326	30.272	6.137	20.644	60.807	100 × Administrative Expenses/Net income from operations
TAT	326	0.027	0.004	0.018	0.039	Revenue/Total assets

The continuous variables are winsorized at the 1% and 99% levels. Obs = the number of observations. SD = standard deviation. Min = the minimum value. Max = the maximum value.

III. Results

Results of baseline regression

Table 2 displays the results of baseline estimations. The coefficients of *LnRegTech* in all the columns are significantly positive at a 5% significance level, suggesting that adopting internal RegTech can significantly reduce bank liquidity risk. Column (2) indicates that if *LnRegTech* increases by one standard deviation, the *LnLDR* will increase by 26.45%, roughly constituting 5.58% ($= 0.373 \times 0.709/4.737$) of the mean value of the *LnLDR*. The results of Columns (3) to (6) indicate that our findings are insensitive to different clustered standard errors, which partially shows the robustness of our conclusion. The results are consistent with Liu, Wang, and Zhang (2024). Although some prior studies have revealed that FinTech reduced banks' liquidity (Tang, Hu, et al. 2024) and spurred corporate risk-taking (Tang, Hou, et al. 2024), our findings support the use of RegTech to alleviate the potential effects of FinTech on financial instability.

Robustness checks

Endogeneity

We initially follow Borusyak and Hull (2023) to employ an instrumental variable (IV) approach and construct a Bartik IV (or Shift-Share IV), which is the product of the lagged first-order internal RegTech index $LnRegTech_{i,t-1}$ (Share) and the first-order time difference of internal RegTech index, $\Delta LnRegTech_{t,t-1}$ (Shift). Bartik IV inherently uses the weighted average of Share and Shift to create a prediction of *LnRegTech* for each observation. Bartik IV is potentially valid since it is uncorrelated with the residuals because the initial share and common shock in Bartik IV are exogenous variables not driven by the current bank's decision-making, which meets the independence assumption. Moreover, as a prediction of *LnRegTech*, the Bartik IV is highly correlated with the internal RegTech level, which satisfies the relevance assumption.

Table 3 displays the results of the two-stage least squares regression. Column (1) shows that the Bartik IV is significantly positive at a 1% level. Meanwhile, the second-stage regression results are

Table 2. Baseline results.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	*LnLDR*	*LnLDR*	*LnLDR*	*LnLDR*	*LnLDR*	*LnLDR*
LnRegTech	0.323**	0.373***	0.373***	0.373***	0.373***	0.373**
	(0.125)	(0.128)	(0.046)	(0.110)	(0.088)	(0.149)
ROA		−0.611	−0.611**	−0.611	−0.611*	−0.611**
		(0.397)	(0.181)	(0.387)	(0.351)	(0.235)
Size		33.134	33.134	33.134	33.134**	33.134
		(29.650)	(33.287)	(36.207)	(16.136)	(59.794)
CAR		0.012	0.012	0.012	0.012	0.012
		(0.044)	(0.042)	(0.048)	(0.050)	(0.055)
NIM		0.419	0.419***	0.419*	0.419*	0.419
		(0.257)	(0.026)	(0.246)	(0.244)	(0.246)
NIIR		0.011	0.011	0.011	0.011*	0.011
		(0.008)	(0.005)	(0.008)	(0.005)	(0.009)
NPGOI		0.004	0.004	0.004	0.004	0.004
		(0.019)	(0.004)	(0.019)	(0.015)	(0.023)
AEGOI		−0.059***	−0.059***	−0.059***	−0.059***	−0.059**
		(0.021)	(0.006)	(0.020)	(0.012)	(0.026)
TAT		−34.278	−34.278***	−34.278	−34.278	−34.278
		(32.226)	(3.201)	(32.277)	(27.120)	(27.082)
Constant	2.999***	−43.314	−43.314	−43.314	−43.314*	−43.314
	(0.676)	(42.783)	(49.063)	(52.041)	(23.990)	(86.671)
Observations	326	326	326	326	326	326
R-squared	0.486	0.510	0.510	0.510	0.510	0.510
Bank fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered standard error	Bank	Bank	Type	Province×Year	Type×Year	Province×Bank

***, **, and * denote significance at the 1% level, 5%, and 10% levels, respectively. Clustered standard errors are reported in parentheses. Type denotes the type of bank. Province implies the province where the headquarters of the bank is located. Column (1) excludes the control variables, and Column (2) corresponds to the model specification described in Eq. (1). The remaining columns differ in clustered standard error.

Table 3. Results of two-stage least squares (2SLS) regression.

VARIABLES	(1) *LnRegTech*	(2) *LnLDR*
LnRegTech		0.913***
		(0.309)
Bartik IV	0.409***	
	(0.133)	
Controls	Yes	Yes
Bank fixed effect	Yes	Yes
Year fixed effects	Yes	Yes
Observations	285	285
C statistic	4.55**	
Kleibergen-Paap rk LM statistic	8.13***	
Cragg-Donald Wald F statistic	70.31***	

***, **, and * denote significance at the 1% level, 5%, and 10% levels, respectively. Bank- and year-fixed effects are considered. The robust standard errors are reported in parentheses. Columns (1) and (2) present the results of the first and second stages of the 2SLS regression, with LnRegTech and LnLDR as the dependent variables, respectively. The rows C statistic, Kleibergen-Paap rk LM statistic, and Cragg-Donald Wald F statistic denote the results of the endogeneity, underidentification, and weak identification tests, respectively.

consistent with Table 2 and confirm our expectations. The C statistic shows that the bank-level RegTech should not be treated as exogenous. Moreover, the Kleibergen-Paap rk LM and Cragg-Donald Wald F statistics suggest no underidentification or weak IV concerns, which shows the IV approach's robustness.

We subsequently employ a RegTech-related quasi-experiment, namely the promotion of Examination and Analysis System Technology (EAST),[1] to explore the role of internal RegTech on bank liquidity risk. We determine the sample period from 2012 to 2022 to ensure sufficient pre-event observations. A staggered difference-in-difference (DID) approach is employed to alleviate endogeneity bias as follows:

$$LnLDR_{it} = \alpha_0 + \alpha_1 EAST_{it} + \alpha_2 Control_{it} + \delta_i + \mu_t + \varepsilon_{it}, \tag{3}$$

where *EAST* is the interaction term of time and treatment variables. Table 4 suggests that the coefficient of EAST is significantly positive for all model specifications. In economic terms, the *LnLDR* increased by 5.83% ($= 0.276 \times 1/4.737$) after adopting EAST, as displayed in Column (2). The results, again, agree with the findings in baseline regression. We further perform parallel trends and placebo tests for robustness checks (see Appendix C). The results support the consistency of our conclusions.

Alternative proxy of bank liquidity risk

We employ the natural logarithm of the liquidity coverage ratio (*LnLCR*) as a proxy of the dependent variable, following the requirement of Basel III. The estimated coefficients are displayed in Column (5) of Table 4, suggesting internal RegTech can significantly decrease liquidity risk. The results again confirm the robustness of the empirical research.

Table 4. Results of the difference-in-difference (DID) approach and other robustness checks.

	(1)	(2)	(3)	(4)	(5)	(6)
		DID estimation			Alternative core variable	Alternative sample period
VARIABLES	*LnLDR*	*LnLDR*	*LnLDR*	*LnLDR*	*LnLCR*	*LnLDR*
EAST	0.240***	0.276***	0.240*	0.276**		
	(0.021)	(0.020)	(0.120)	(0.126)		
LnRegTech					0.080**	0.333**
					(0.037)	(0.159)
Constant	4.862***	−8.811	4.862***	−8.811	−5.050	−53.440
	(0.014)	(27.265)	(0.084)	(37.982)	(19.024)	(57.256)
Controls	No	Yes	No	Yes	Yes	Yes
Observations	439	439	439	439	274	285
R-squared	0.456	0.492	0.492	0.491	0.731	0.503
Bank fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered standard error	Type	Type	Province	Province	Bank	Bank

***, **, and * denote significance at the 1% level, 5%, and 10% levels, respectively. Bank- and year-fixed effects are considered. Type denotes the type of bank. Province implies the province where the headquarters of the bank is located. *EAST* represents the promotion of Examination and Analysis System Technology. EAST is assigned to 1 if the corresponding bank has been included in the EAST and 0 otherwise. *LnLCR* indicates the natural logarithm of the liquidity coverage ratio, computed as $LnLCR = \ln\left(100 \times \frac{\text{High quality liquid asset amount}}{\text{Total net cash flow amout in a 30-day stress period}}\right)$.

[1]The institutional background of EAST is clarified in the Appendix B.

Table 5. Results of channel test and cross-sectional analysis.

	(1)	(2)	(3)	(4)	(5)	(6)
		Channel test		Compliance	Regulation	Technological foundation
VARIABLES	*LnAAP*	*LnAAP*	*LnAAP*	*LnLDR*	*LnLDR*	*LnLDR*
LnRegTech	−0.570***	−0.570**	−0.570***			
	(0.188)	(0.166)	(0.126)			
LnCom				0.366**		
				(0.151)		
LnReg					0.216	
					(0.129)	
LnTech						0.341***
						(0.114)
Constant	−185.426*	−185.426	−185.426	−52.531	−31.332	−38.993
	(106.822)	(106.790)	(124.584)	(55.182)	(49.070)	(52.205)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	326	326	326	326	326	326
R-squared	0.781	0.781	0.781	0.510	0.503	0.509
Bank fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered standard error	Bank	Type	Province	Bank	Bank	Bank

***, **, and * denote significance at the 1% level, 5%, and 10% levels, respectively. Bank- and year-fixed effects are considered. Type denotes the type of bank. Province implies the province where the headquarters of the bank is located. The columns of Compliance, Regulation, and Technological foundation represent the results corresponding to the cases employing the three application-scenario-related subindices (i.e. compliance application, regulatory application, and technological foundation as the core variable. The three RegTech subindices are measured by the natural logarithm of the keyword frequencies, denoted as *LnCom*, *LnReg*, and *LnTech*, respectively.

Alternative sample period

The Chinese A-share market experienced a historic fall in June 2015. The huge market fluctuation may spillover to the banking sector and lead to a liquidity crisis. We, therefore, remove the period of the extraordinary fall (i.e. the year 2015) and show the results in Column (6) of Table 4. The significantly positive coefficient of internal RegTech again confirms the robustness of our results.

Potential channels

The nexus between internal and external RegTech suggests that the former can boost the automatic and timely regulation of banks' behaviours, contributing to enhanced regulatory capability. The tightened regulation and sanctions may further discipline banks' risk-taking (Gao et al. 2020).

To validate our conjecture, we examine the effects of internal RegTech on regulatory capability, proxied by the natural logarithm of administrative penalty (*LnAAP*) in Columns (1) - (3) in Table 5. The results suggest that internal RegTech significantly decreases *LnAAP* at the 5% level, and the coefficients are −0.570 for all columns.[2] A possible reason is that internal RegTech can help the regulators accurately identify banks' misconduct and deter banks' risky behaviours.

Cross-sectional analysis

Internal RegTech may play diverse roles and impacts in different application scenarios within the banking industry. We further separate the internal RegTech index into three subindices based on the application scenarios: compliance application, regulatory application, and technological foundation. Columns (4) to (6) in Table 5 display the results for RegTech subindices, revealing that the compliance and technological foundation are more profound in affecting banks' liquidity risk. A possible explanation is their relatively mature and widespread applications compared to supervision usage.

IV. Conclusions

In this paper, we explore the causal effect of internal RegTech on bank liquidity risk. Based on a dataset of Chinese listed banks from 2015 to 2022, we reveal a significant mitigation effect of internal RegTech on bank liquidity risk. The finding remains robust after alleviating the endogeneity issue and under alternative proxy of the dependent variable and different sample periods. A possible channel is that internal RegTech boosts the regulatory capability and mitigates banks' risky behaviours. The

[2]See additional channel tests under the endogeneity concern in Appendix D.

compliance and technological foundations sub-indices are more profound in affecting bank liquidity risk.

Our research offers valuable implications for banks and financial regulators. For banks, investment in internal RegTech should be encouraged to lower compliance costs and improve liquidity risk management. Further explorations on supervision usage are expected. From a regulatory standpoint, advanced technologies can be incorporated into regulatory practice to enforce penetrating supervision and bridge the regulatory gap. The enhanced external regulatory capability can boost internal RegTech's effect on banks' liquidity risk control.

Our research still suffers from some limitations. First, we consider only the listed banks due to data availability. Second, more channels within the nexus between RegTech and bank liquidity risk warrant further investigations.

Disclosure statement

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