Digital Expertise of Corporate Leaders and Bank Performance: A Governance Perspective from China

Zhaowei Ma
School of Finance, Nankai University, Tianjin, China

Abstract: We examine the causal impact of corporate leaders' digital expertise on bank performance in China's hybrid banking system. Using 3,585 bank-year observations from 353 commercial banks over 2008-2022, we find that corporate leaders' digital expertise is positively associated with bank performance, with subsample analysis indicating that the primary effect stems from board-level leadership. Findings are robust to controlling for a broad set of both country and bank determinants, accounting for endogeneity by using instrument variables - the density of mobile phone base stations-and conducting difference-in-difference analysis. Results extend upper echelons theory to the fintech era and have implications for regulate strategies, including talent redistribution, bank governance and management.

Keywords: Banking; Performance; Digital Expertise; Fintech; Governance

1. Introduction

With the application of digital technology, like AI, blockchain, and big data analytics, digital finance has developed rapidly in China in the last decade. The digital revolution has fundamentally reshaped banking, demanding institutions to adopt technologies to enhance efficiency and risk management. In China, this transformation is uniquely accelerated by the Government Report in 2015 and the Plan for Promoting Financial Inclusive Development (2016–2020), which emphasized the importance of developing digital finance, meeting the growing financial needs of the people, and improving the coverage, accessibility, and satisfaction of financial services. However, while infrastructure investment is critical, the human capital behind strategic decisions. This oversight is striking given China’s hybrid governance landscape, where state-owned banks coexist with joint-stock and city-commercial banks, each navigating distinct pressures to balance innovation with regulatory compliance.

This paper attempts to fill the gap by analyzing the effect of corporate leaders' digital expertise on bank performance and further exploring the potential mechanisms. Using textual analysis to extract the corporate leaders' information from banking annual report and match the banking accounting data, we last draw from 353 commercial banks over 2008-2022. Findings show that increasing the number of corporate leaders with digital expertise is positively linked to bank profitability and decreases their failure and liquidity risk, with subsample analysis indicating that the primary effect stems from board-level leadership.

The results are robust to a variety of test, including additional bank and macroeconomic controls, different digital expertise measure, alternative sample compositions, difference-in-difference method and an instrumental variable analysis to mitigate potential endogeneity concerns.

Our paper contributes to the literature in three ways. Firstly, we extend upper echelons theory by conceptualizing digital expertise as a critical cognitive dimension in the fintech era.

Secondly, we provide a new view to studying bank performance and risk by focusing on the expertise of bank managers, while the previous scholars studied on financial and legal expertise.

Lastly, our paper provides a new insight for understanding we provide a supplement to the corporate governance of Chinese commercial banks, namely, introducing talents with digital backgrounds can not only improve innovation, but also increase bank performance and reduce risks.

The remainder of the paper is organized as follows. Section 2 reviews the upper echelons theory, corporate governance in banking and develops the empirical hypotheses. Section 3 describes the data and key variables used in the analysis. Section 4 discusses the main results, robustness tests, subsample analysis and endogeneity and channel analysis. Section 5 concludes.

2. Literature Review and Hypothesis Development

2.1 Upper Echelons Theory

The upper echelons theory, originally anchored by Hambrick and Mason's (1984), emphasizes how CEOs' and senior executives' demographic characteristics systematically influence organizational outcomes through their cognitive frameworks and value systems. Subsequent research has extended this theoretical paradigm, with recent studies also focusing on the impact of board digital expertise on digital innovation [1].

A stream of scholars has examined the impact of managerial educational background on firm performance [2]. Another stream of research on board diversity has revealed significant effects arising from nationality heterogeneity [3] and cultural differences, with cross-country studies showing that cultural values affect bank failure risks globally [4]. In recent years, increasing attention has been paid to the impact of gender diversity. For instance, studies using quantile regression methods have demonstrated a positive relationship between boardroom gender diversity and firm performance [5]; other research explores risk mitigation mechanisms through gender-diverse governance, while some examine the effect of hedge fund activism on gender diversity. Additionally, gender diversity has been found to exert significant impacts on firm risk and executive compensation [6]. With the rising prominence of ecological civilization, parallel studies have focused on corporate social responsibility and ESG performance.

A growing body of emerging scholarship explores specialized executive attributes, including financial expertise, foreign experience, which is closely associated with CEO compensation levels [7], compensation structure, behavioral biases such as overconfidence, a trait that significantly influences strategic risk-taking and firm performance [7], as well as military and legal expertise, with legal expertise on audit committees enhancing financial reporting quality [8].

This literature remains notably silent on digital competencies despite accelerating financial digitalization – a gap our study addresses.

2.2 Corporate Governance in Banking

Bank governance exhibits unique complexities due to heightened information asymmetry, intense regulatory scrutiny, and conflicting stakeholder interests. Economic policy uncertainty further exacerbates these complexities by driving banks to hoard liquidity, and global events like the COVID-19 pandemic have also highlighted the cross-country differences in bank systemic risk [9]. Meanwhile, the Chinese context introduces additional complexities, as state-controlled entities operate alongside commercial institutions amid ongoing financial reforms.

Existing studies predominantly focus on traditional board characteristics. Specifically, research shows that CEOs with high-quality MBA education outperform their peers and adopt riskier business models that enhance performance; other studies have identified an inverted U-shaped relationship between bank performance and board size through two-stage estimation. In contrast, some research finds that board size exerts a negative impact on performance, with additional effects from board meeting frequency and independence. Beyond board size, board structure and director expertise also play crucial roles in the advisory function of outside directors. Additionally, factors such as financial advice affect bank profits [10], product diversification influences bank performance with ownership structure as a moderator [11], and the industry expertise of independent directors strengthens board monitoring effectiveness [11].

This established framework overlooks digital leadership effects – a critical omission given China's "Fintech 2025" initiative.

2.3 Hypothesis Development

Building on these foundations, we propose that digital expertise constitutes a critical cognitive dimension in financial governance. In China, banking institutions confront acute information asymmetry, intense regulatory scrutiny, and conflicting stakeholder interests; in this context, managers' ability to interpret digital signals serves as a governance mechanism that reduces operational uncertainty and enhances performance.

Existing studies have shown that specialized expertise (e.g., financial and legal expertise) equips executives to address industry-specific challenges. However, the role of digital expertise remains insufficiently explored, despite its growing significance in driving digital innovation in commercial banks.

We thus posit:

H1: Executives' digital expertise is positively associated with bank performance.

Digital expertise creates distinct value through three mechanisms: First, it empowers leaders to prioritize technological innovation through R&D investments that transform abstract technological knowledge (e.g., AI algorithms, blockchain protocols) into patentable solutions, thereby reducing dependence on external fintech vendors while enhancing operational self-sufficiency. This innovation-driven governance creates an environment conducive to technological commercialization, directly reinforcing banks' innovation capability to enhance profit margins through proprietary product development – termed the patent channel.

Second, executives with digital expertise implement machine learning-enhanced credit assessment systems, enabling granular risk detection beyond conventional financial analysis. This technological capacity allows strategic expansion of the loan-to-deposit ratio beyond industry benchmarks in two complementary ways: 1) identifying creditworthy borrowers overlooked by traditional methods under China's macroprudential framework, and 2) containing non-performing loans (NPLs) through predictive default modeling. The resultant risk-adjusted yield premium emerges from optimized credit allocation efficiency – conceptualized as the LDR channel.

Third, digital leadership enables algorithm-driven liquidity management systems that optimize compliance with China's tiered capital buffer requirements by dynamically adjusting reserve allocations in real time while identifying underutilized liquidity pools. This precision governance releases trapped capital for redeployment into high-yield assets—such as interbank peer-to-peer lending or structured wealth management products—without breaching regulatory thresholds. We term this the liquidity optimization channel, where digital expertise transforms regulatory constraints into opportunities for profit-generating liquidity repositioning.

3. Literature Review

3.1 Bank Performance

As critical intermediaries in financial systems, banks' profit generation and risk-taking behaviors warrant separate investigation. Although banking institutions have become increasingly complex, profitability remains the fundamental driver of bank performance. Following previous studies, we select *ROA* – calculated as net profit divided by total assets – as the main proxy variable. This metric has been extensively validated in banking research. To ensure robustness, we supplement this with two alternative proxies: pre-provision profit ratio, *PPR*, measured by operating income divided by total assets, and income-to-asset ratio, *Income*, measured as operating income divided by total assets.

We measure bank risk using two complementary proxies: *Lnzscore*, which captures both profitability and capital adequacy, with higher values indicating greater distance from insolvency, and liquidity risk (LR), adopting Berger and Bouwman's liquidity creation methodology, where positive values denote liquidity mismatch exposure. For a detailed description of the variables see Table-1.

3.2 Digital Expertise of Corporate Leaders

We use two types of variables to measure the digital expertise. We manually collected bank annual reports from 2008 to 2022 and extracted information on boards, supervisors and senior executives of each bank. We operationalize boards, supervisors and senior executives with digital expertise (*Dig All*) as the total number of boards, supervisors and senior executives with digital expertise, *DFR* as the ratio of the number of boards, supervisors and senior executives with digital expertise to the total number of boards, supervisors and senior executives, *Dig Board Num* as the number of boards with digital expertise, *Dig Sup Num* as the number of supervisors with digital expertise, *Dig Exe Num* as the number of executives with digital expertise. Following the previous digital expertise literatures [12], we consider members with digital expertise if a) their current or past job titles contain the keywords "technology", "information", or "digital"; b) they have an academic degree related to digital technologies; or c) they hold or have held a position in a bank department or division related to digital technologies. Following the previous studies, we missing digital expertise values to zero and replace missing leadership size data with bank-year averages. For a detailed description of the variables see Table-1.

3.3 Bank Characteristics

To explore t how digital expertise affects bank performance, we manually collect the number of patents for inventions to measure the bank's innovation capability (*Patent*), which equals the natural logarithm of one plus patent grants, liquidity creation (*LC*), which measures the bank liquidity creation capacity loan-to-deposit ratio (*LDR*), which measures the ratio of total loan to total deposit.

Following previous studies [13], we include total asset (*Size*), total loan (*Loan*), deposit (*Depo*), leverage (*Lev*), nonperforming loan (*Npl*), the total number of boards, supervisors and senior executives (*All Num*) as variables to control bank characteristics that may influence bank performance. To control macroeconomic influences, we also control for GDP growth ratio (*GDP*), broad measure of money supply (*M2*), inflation (*CPI*). For a detailed description of the variables see Table-1.

3.4 Descriptive Statistics

Our final sample contains 3585 bank-year observations for 353 banks covering the period of 2008–2022, Table-2 shows the descriptive statistics of our sample. For our key dependent variables, the average value of *ROA* is 0.873, pre-provision profit ratio (*PPR*) is 1.131, income-to-asset ratio (*Income*) is 2.918, *Lnzscore* is 4.349, liquidity risk (*LR*) is 0.822. For the key independent variables, the average value of *Dig All* is 0.787, digital financial ratio (*DFR*) is 2.891.

Turning to the bank controls. We find that the average bank in our sample has log of total assets (*Size*) of 24.965, loan ratio (*Loan*) of 51.045%, leverage (*Lev*) of 92.292%, deposit ratio (*Depo*) of 75.524%, *Npl* of 1.823% and *All Num* of 24.427. These suggest that the average bank tends to be large, well-capitalized, and maintains sound fundamentals, although these averages may mask important differences across banks and over time.

Table 1. Definition of Variables

Variable	Definition	Unit
Dependent variables		
ROA	The ratio of net profit to total assets.	%
PPR	The ratio of operating profit to total assets.	%
Income	The ratio of operating income to total assets.	%
Lnzscore	The nature logarithm of Bank's ROA plus the capital asset ratio divided by the stdv of ROA over a three years' period.	Natural Logarithm
LR	Liquidity Asset divided by the liquidity liability.	%
Independent variables		
Dig All	Total number of boards, supervisors and senior executives with digital expertise.	Natural Numbers
DFR	The ratio of the number of boards, supervisors and senior executives with digital expertise to the total number of boards, supervisors and senior executives.	%
Dig Board Num	Total number of boards with digital expertise.	Natural Numbers
Dig Sup Num	Total number of supervisors with digital expertise.	Natural Numbers
Dig Exe Num	Total number of senior executives with digital expertise.	Natural Numbers
Other variables		
Patent	The nature logarithm of one plus the number of bank's patents.	Natural Logarithm
LDR	The ratio of total loan to total deposit.	%
LC	A bank's total bank liquidity creation measure normalized by the total asset size of a bank.	%
LC Asset	A bank's bank liquidity creation measure including only asset-side activities normalized by the total asset size of a bank.	%

LC Liab	A bank's bank liquidity creation measure including only liability-side activities normalized by the total asset size of a bank.	%
Size	The nature logarithm of bank's total assets.	Natural Logarithm
Loan	The ratio of total loans to total assets.	%
Lev	The ratio of total liabilities to total assets.	%
Depo	The ratio of deposit to total assets.	%
Npl	The ratio of bank nonperforming loan to total assets.	%
All Num	The total number of boards, supervisors and senior executives.	Natural Numbers
Board Num	The total number of banks' boards.	Natural Numbers
Sup Num	The total number of banks' supervisors.	Natural Numbers
Exe Num	The total number of banks' senior executives.	Natural Numbers
GDP	Real gross domestic product (GDP) growth ratio.	%
M2	The growth of macro monetary quantity.	%
CPI	Inflation growth, measured by the growth of customer purchase index.	%
Public	A dummy variable equal to 1 if an individual bank is a publicly listed in a particular year.	Natural Numbers
Own	A dummy variable coded 1 if a specific bank is a state-owned enterprise in a given year, and 0 otherwise.	Natural Numbers
Type	Indicator variable: coded 1 if the bank is a state-owned bank, 2 if it is a joint-stock bank, 3 if it is a city commercial bank, and 4 if it is a rural commercial bank.	Natural Numbers

Table 2. Summary Statistics

	N	Mean	SD	Min	Max
ROA	3585	0.873	0.405	0.017	2.048
PPR	3585	1.131	0.546	0.025	2.723
Income	3585	2.918	0.870	1.342	5.849
Lnzscore	3585	4.349	0.954	2.351	6.869
LR	3585	0.822	0.148	0.466	1.256
Dig All	3585	0.787	1.689	0	11
DFR	3585	2.891	6.174	0	40.741
Dig Board Num	3585	0.414	1.023	0	9
Dig Sup Num	3585	0.191	0.570	0	4
Dig Exe Num	3585	0.226	0.589	0	5
Patent	3585	0.196	0.738	0	4.382
LDR	3585	69.022	11.759	39.205	102.52
LC	3585	12.022	10.517	-13.859	42.101
LC Asset	3585	-20.917	8.341	-39.299	3.952
LC Liab	3585	32.941	7.132	11.402	43.969
Size	3585	24.965	1.663	22.046	30.098
Loan	3585	51.045	9.951	24.543	73.459
Lev	3585	92.292	2.010	85.167	96.363
Depo	3585	75.524	10.586	47.055	91.702
Npl	3585	1.823	1.233	0.140	8.820
All Num	3585	24.427	4.213	3	56
Board Num	3585	12.271	2.454	1	21
Sup Num	3585	7.217	1.584	1	17
Exe Num	3585	7.210	2.398	1	38
GDP	3585	10.213	4.353	2.742	23.083
M2	3585	12.378	4.129	8.271	26.616

CPI	3585	-0.001	0.017	-0.062	0.040
Public	3585	0.220	0.415	0	1
Own	3585	0.441	0.497	0	1
Type	3585	3.442	0.700	1	4

4. Empirical Analysis and Results

4.1 Main Test

Following the previous studies, we specify the OLS model to explore the effect of digital expertise (*Dig All*) on the bank performance. The baseline model is as follows:

$$Bank\ Performance_{i,t} = \beta_0 Dig\ All_{i,t-1} + \beta_1 Control_{i,t-1} + \gamma_{t-1} + \epsilon_i + \varepsilon_{i,t-1}\ (1)$$

where $Bank\ Performance_{i,t}$ denotes the bank performance for bank i in year t, including *ROA*, *PPR*, *Income*, *Lnzscore* and *LR*. $Dig\ All_{i,t-1}$ represents the measure of digital expertise for bank i in year t-1.$Control_{i,t-1}$ is lagged control variable, including *Size*, *Loan*, *Lev*, *NPL*, *All Num*, *GDP*, *M2* and *CPI*. We also include bank and year fixed effects to address the possible omitted variable problem, and employ adjust standard errors clustered by bank. We winsorize the continuous variables at 1% in both tails to remove outliers.

Table-3 presents baseline regression results examining the relationship between digital expertise (*Dig All*) and bank performance. We employ a staggered estimation approach to isolate the marginal effects of digital leadership while addressing potential confounders. The column (1), we incorporate the bank and time fixed effects to control for unobserved heterogeneity, the estimated coefficient is positive and significant at the 1% level. An increase in *Dig All* by one standard deviation is associated with an increase in ROA by 8.72%. In the column (2), bank-level control variables are introduced, the results remain positive and significant. In the column (3), the macroeconomic factors are included, however, it can be observed that the macroeconomic factors were absorbed by the time effects. To disentangle macro effects, column (4) replaces time fixed effects with direct macroeconomic controls. The *Dig All* coefficient still positive but significant at 5% level, rejecting concerns about omitted variable bias from economic cycles. In columns (5)-(6) we replace the dependent *ROA* with other two measures to validate robustness: *PPR* and *Income*. Obviously, the coefficients remain positive and statistically significant at 1% level. One-standard-deviation increases in *Dig All* result in 3.26% increase in bank *PPR* and 3.82% increase in bank *Income*, respectively. In column (7)-(8), we further examine the dual impact of digital expertise on bank risk profiles, the results show that the coefficient of *Lnzscore* is 0.0250, positive and significant at 10% level, and the coefficient of *LR* is negative and significant at 1% level, which reveals that digital leadership accumulation simultaneously mitigates both insolvency risk and liquidity risk.

The baseline results support our hypothesis that digital expertise is positively associated with bank performance.

Table 3. Effects of Digital Expertise on Bank Performance – Main Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	*ROA*	*ROA*	*ROA*	*ROA*	*PPR*	*Income*	*Lnzscore*	*LR*
Dig All	0.0209***	0.0177***	0.0177***	0.0130**	0.0218***	0.0660***	0.0250*	-0.0124***
	(3.2929)	(3.3948)	(3.3948)	(2.5707)	(3.2094)	(6.6950)	(1.6562)	(-5.1549)
Size		-0.0027	-0.0027	-0.1023***	-0.0032	0.1211*	0.0392	0.0441**
		(-0.0634)	(-0.0634)	(-3.7426)	(-0.0605)	(1.7123)	(0.5123)	(2.5548)
Loan		0.0013	0.0013	-0.0048***	0.0028	0.0206***	0.0057	0.0041***
		(0.7460)	(0.7460)	(-3.2055)	(1.2729)	(6.5646)	(1.4755)	(5.8652)
Lev		-0.0090	-0.0090	-0.0164***	-0.0090	-0.0360***	-0.0190	-0.0024
		(-1.4982)	(-1.4982)	(-2.6025)	(-1.2132)	(-2.8234)	(-1.3639)	(-0.8723)
Depo		0.0032**	0.0032**	0.0029*	0.0034*	0.0007	0.0027	-0.0046***
		(2.2608)	(2.2608)	(1.9303)	(1.8016)	(0.2365)	(0.7538)	(-6.9959)
Npl		-0.1006***	-0.1006***	-0.1089***	-0.1267***	-0.0459***	-0.0721***	0.0018
		(-11.1236)	(-11.1236)	(-12.3619)	(-10.6390)	(-3.7891)	(-3.0293)	(0.4880)
All Num		0.0001	0.0001	-0.0018	0.0002	0.0003	0.0109*	-0.0002

		(0.0673)	(0.0673)	(-0.8299)	(0.0626)	(0.0875)	(1.7132)	(-0.2118)
GDP			0.0000	0.0057***	0.0000	0.0000	0.0000	0.0000
			(.)	(5.1421)	(.)	(.)	(.)	(.)
M2			0.0000	0.0251***	0.0000	0.0000	0.0000	0.0000
			(.)	(8.5368)	(.)	(.)	(.)	(.)
CPI			0.0000	1.5502***	0.0000	0.0000	0.0000	0.0000
			(.)	(6.1411)	(.)	(.)	(.)	(.)
Constant	0.8568***	1.6274	1.6274	4.8338***	1.8544	2.1417	4.4704*	0.0826
	(171.1467)	(1.2800)	(1.2800)	(4.9315)	(1.1707)	(0.9851)	(1.9528)	(0.1841)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Adjusted R2	0.608	0.666	0.666	0.624	0.698	0.773	0.342	0.435
Observations	3,585	3,585	3,585	3,585	3,585	3,585	3,585	3,585

4.2 Robustness Test

4.2.1 Alternative measurement of digital expertise

To ensure the robustness of our findings, we implement an alternative measure for the independent variable: *DFR*, which is defined the ratio of the number of boards, supervisors and senior executives with digital expertise to the total number of boards, supervisors and senior executives. As shown in Table-4, the results remain statistically and economically consistent with the baseline model.

Table 4. Effects of Digital Expertise on Bank Performance – Alternative Digital Expertise Variables

	(1)	(2)	(3)	(4)
VARIABLES	*ROA*	*Income*	*PPR*	*LR*
DFR	0.0042***	0.0171***	0.0051***	-0.0035***
	(2.8355)	(6.2969)	(2.6594)	(-5.1957)
Size	-0.0021	0.1213*	-0.0024	0.0444**
	(-0.0499)	(1.7130)	(-0.0459)	(2.5713)
Loan	0.0013	0.0206***	0.0028	0.0041***
	(0.7639)	(6.5618)	(1.2903)	(5.8490)
Lev	-0.0092	-0.0363***	-0.0092	-0.0024
	(-1.5278)	(-2.8428)	(-1.2445)	(-0.8755)
Depo	0.0032**	0.0007	0.0033*	-0.0046***
	(2.2445)	(0.2511)	(1.7857)	(-7.0430)
Npl	-0.1007***	-0.0463***	-0.1269***	0.0018
	(-11.1125)	(-3.8140)	(-10.6276)	(0.4969)
All Num	0.0009	0.0029	0.0011	-0.0007
	(0.4413)	(0.7511)	(0.4198)	(-0.6927)
Constant	1.6144	2.0972	1.8383	0.0903
	(1.2685)	(0.9626)	(1.1593)	(0.2017)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R2	0.665	0.773	0.697	0.436
Observations	3,585	3,585	3,585	3,585

4.2.2 Subsample analysis

To answer the question "Which governance tier of digital expertise affects profit margins?". We conduct the disaggregated analyses of digital expertise origins in Table-5, examining distinct impacts from board members (*Dig Board Num*), supervisors (*Dig Sup Num*), and executives (*Dig Exe Num*) on bank profitability. Our findings reveal a hierarchical dominance effect in digital leadership efficacy: The coefficient for Dig_Board_Num reaches 0.0282, positive and significant at 1% level, persists after macroeconomic controls and consistent with strategic decision-making theory (Adams et al., 2010). In column (3)-(4), we discover that the coefficient of *Dig Sup Num* is positive and significant at 5% level, but the significance disappears after controlling the macro-economic, and in column (7)-(8), we incorporate three tiers to review the impact, the coefficient significance of *Dig Sup Num* also disappears. This suggests supervisors' digital expertise primarily facilitates regulatory compliance rather than profit generation. We also test the role of executives, but the results insignificant, even after controlling macro-economic and incorporate all three tiers.

Table 5. Effects of Digital Expertise on Bank Performance – Subsample Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	*ROA*	*ROA*	*ROA*	*ROA*	*ROA*	*ROA*	*ROA*	*ROA*
Dig Board Num	0.0286***	0.0230***					0.0282***	0.0232***
	(3.8152)	(3.1947)					(3.4968)	(3.0341)
Dig Sup Num			0.0280**	0.0181			0.0178	0.0097
			(1.9887)	(1.3524)			(1.2519)	(0.6908)
Dig Exe Num					0.0074	0.0047	-0.0140	-0.0107
					(0.5045)	(0.3164)	(-0.8761)	(-0.6531)
Size	-0.0027	-0.1019***	0.0029	-0.0963***	0.0035	-0.0938***	-0.0008	-0.0986***
	(-0.0642)	(-3.6569)	(0.0699)	(-3.6916)	(0.0848)	(-3.4494)	(-0.0203)	(-3.4578)
Loan	0.0013	-0.0049***	0.0013	-0.0047***	0.0014	-0.0046***	0.0011	-0.0049***
	(0.7257)	(-3.2494)	(0.7731)	(-3.1127)	(0.7922)	(-3.0659)	(0.6605)	(-3.3478)
Lev	-0.0093	-0.0168***	-0.0097	-0.0167***	-0.0100*	-0.0174***	-0.0090	-0.0165***
	(-1.5637)	(-2.7150)	(-1.5946)	(-2.6284)	(-1.6569)	(-2.7434)	(-1.5263)	(-2.6816)
Depo	0.0033**	0.0030*	0.0031**	0.0029*	0.0030**	0.0028*	0.0034**	0.0031**
	(2.3247)	(1.9544)	(2.1543)	(1.9033)	(2.0620)	(1.8125)	(2.4215)	(2.0781)
Npl	-0.1006***	-0.1091***	-0.1008***	-0.1088***	-0.1013***	-0.1096***	-0.1003***	-0.1089***
	(-10.9864)	(-12.2201)	(-11.1380)	(-12.3464)	(-10.9152)	(-12.1736)	(-11.0960)	(-12.2108)
Board Num	0.0055*	0.0001					0.0082**	0.0038
	(1.7045)	(0.0393)					(2.3139)	(0.9365)
Sup Num			-0.0066	-0.0126**			-0.0107*	-0.0148**
			(-1.2350)	(-2.1992)			(-1.9168)	(-2.3723)
Exe Num					-0.0014	-0.0012	-0.0011	-0.0003
					(-0.4975)	(-0.3787)	(-0.3875)	(-0.1086)
GDP	0.0000	0.0056***	0.0000	0.0056***	0.0000	0.0057***	0.0000	0.0053***
	(.)	(5.0288)	(.)	(5.0846)	(.)	(5.2397)	(.)	(4.7714)
M2	0.0000	0.0251***	0.0000	0.0246***	0.0000	0.0247***	0.0000	0.0247***
	(.)	(8.4417)	(.)	(8.5629)	(.)	(8.4817)	(.)	(8.5270)
CPI	0.0000	1.5763***	0.0000	1.5132***	0.0000	1.5354***	0.0000	1.5678***
	(.)	(6.1328)	(.)	(6.0060)	(.)	(6.0842)	(.)	(6.1448)
Constant	1.5852	4.8106***	1.6175	4.7642***	1.6074	4.6913***	1.5676	4.7653***
	(1.2576)	(4.7962)	(1.2887)	(4.9589)	(1.2679)	(4.7630)	(1.2641)	(4.7462)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	NO	Yes	NO	Yes	NO	Yes	NO
Adjusted R2	0.667	0.624	0.665	0.624	0.664	0.623	0.668	0.625
Observations	3,585	3,585	3,585	3,585	3,585	3,585	3,585	3,585

Next, we test the heterogeneous effect of managers with digital expertise on bank performance from three aspects. We expect that the impact of the digital expertise would differ across the banks with different types. We divide the sample into four type groups. The results in Table-6 reveal significant heterogeneity in the relationship across bank types. Column (1) represent state-owned large banks, the coefficient of *Dig All* is positive but statistically insignificant, suggesting limited short-term effects of digital expertise on profitability in these institutions, likely due to their established infrastructure and slower adoption of disruptive innovations. Conversely, joint-stock banks, in column (2), exhibit a negative yet insignificant coefficient, which may reflect. Notably, in column (3)-(4), city commercial banks and rural commercial banks demonstrate statistically significant positive effects. This highlights that digital talent contributes more substantially to ROA in smaller, regionally focused banks, possibly because these institutions leverage digitalization to enhance operational efficiency.

We also expect that the impact of the digital expertise would differ across banks by public and non-public and state-own and non-state-own in Table-7. Column (1)-(2), we study the impact of *Dig All* on both listed and non-listed bank, the results reveal that the non-listed banks exhibit stronger profitability sensitivity to digital expertise, consistent with operational agility enabling faster technology absorption. Conversely, the muted response among listed banks reflects capital market pressures prioritizing short-term stability over innovation cycles.

In column (3)-(4) of Table-7, we further explore the difference between state-owned and non-state-owned bank, state-owned banks show a significant positive effect of *Dig All* on *ROA*, aligning with their access to state-backed resources and policy-driven digital initiatives. The effect for non-state-owned banks is positive but statistically insignificant, possibly due to fragmented governance or competitive constraints.

To conclude, non-listed banks benefit from agility, while state-owned banks capitalize on policy support. Therefore, listed institutions must balance innovation with shareholder expectations, and non-state-owned banks require governance reforms to align digital investments with strategic goals.

Table 6. Effects of Digital Expertise on Bank Performance – Subsample Analysis

	(1)	(2)	(3)	(4)
	Type = 1	*Type = 2*	*Type = 3*	*Type = 4*
VARIABLES	*ROA*	*ROA*	*ROA*	*ROA*
Dig All	0.0040	-0.0113	0.0152*	0.0207***
	(0.8521)	(-1.2229)	(1.8655)	(2.7417)
Size	0.0989*	0.3048**	0.0803	-0.0350
	(2.3583)	(2.4834)	(1.3663)	(-0.4147)
Loan	0.0118**	0.0027	0.0008	0.0007
	(3.7508)	(0.4130)	(0.3038)	(0.3015)
Lev	0.0119	-0.0109	-0.0071	-0.0079
	(0.5351)	(-0.7737)	(-0.9119)	(-0.8960)
Depo	0.0045	0.0043	0.0039*	0.0033*
	(1.2901)	(1.2413)	(1.7341)	(1.7982)
Npl	-0.0931***	-0.0885***	-0.1000***	-0.1070***
	(-5.1785)	(-3.8844)	(-5.6385)	(-10.5379)
All Num	0.0018	-0.0047	0.0043	-0.0020
	(1.1275)	(-1.1111)	(1.3427)	(-0.8252)
Constant	-3.9679	-6.8851*	-0.8316	2.4354
	(-1.8013)	(-2.0717)	(-0.4729)	(1.1128)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R2	0.972	0.763	0.636	0.699
Observations	86	177	1,389	1,933

Table 7. Effects of Digital Expertise on Bank Performance – Subsample Analysis

	(1)	(2)	(3)	(4)
	Public = 0	*Public = 1*	*Own = 0*	*Own = 1*
VARIABLES	*ROA*	*ROA*	*ROA*	*ROA*
Dig All	0.0227***	-0.0094	0.0122	0.0136**
	(2.8174)	(-1.3886)	(1.2787)	(2.0871)
Size	0.0465	-0.0077	0.0169	-0.0169
	(0.9258)	(-0.1142)	(0.2182)	(-0.3443)
Loan	0.0012	-0.0003	0.0011	-0.0004

	(0.6478)	(-0.0659)	(0.5015)	(-0.1363)
Lev	-0.0051	-0.0205	-0.0067	-0.0093
	(-0.7859)	(-1.4783)	(-0.7585)	(-1.1022)
Depo	0.0051***	0.0010	0.0045**	0.0034
	(3.3275)	(0.3684)	(2.1823)	(1.6176)
Npl	-0.1092***	-0.0455**	-0.1192***	-0.0751***
	(-11.2819)	(-2.3306)	(-11.2478)	(-4.7586)
All Num	0.0003	-0.0012	-0.0004	-0.0006
	(0.1461)	(-0.3123)	(-0.1409)	(-0.2012)
Constant	-0.0587	3.0656	0.9527	2.0117
	(-0.0407)	(1.2060)	(0.4259)	(1.3165)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R2	0.689	0.602	0.708	0.579
Observations	2,795	790	2,004	1,581

4.3 Endogeneity

In the baseline regression, we show that firms that pose managers with digital expertise are associated with more profit's outputs in the following year. However, the results could be biased by potential endogeneity issues. For instance, there may be omitted variables that affect both the bank's performance and the number of managers with digital expertise. Such omitted variables can be observable bank characteristics or management characteristics, or unobservable factors such as macroeconomic changes or institutional variations. Although we have adopted some measures to avoid, there are still some potential issues. We address the potential endogeneity issue with a difference-in-differences (DID) design leveraging China's Cybersecurity Law enacted in November 2016. Furthermore, we include an instrument variable estimation in Table-8.

4.3.1 Difference-in-difference analysis

To mitigate potential endogeneity concerns, we implement a difference-in-differences (DID) design leveraging China's Cybersecurity Law enacted in November 2016. This legislation, promulgated by the Standing Committee of the National People's Congress (SCNPC, 2016), established national standards for network security while mandating enhanced information technology infrastructure in critical sectors. In the article 13 of the Law, the state supports the research and development of Internet products and service, commercial banks, as a critical part of the financial system, should actively respond to the national call, develop a secure, stable, flexible, and efficient information technology system that supports effective business operations and risk management.

Specifically, we examine the effect of exogenous growth in digital expertise on bank performance by incorporating an interaction term between Post and Treat. Post is a dummy variable equal to 1 for the period 2016 to 2022 and 0 otherwise. Treat, meanwhile, is a dummy variable coded 1 for banks that lacked managers with digital expertise in the year the Law was enacted but appointed such directors to their management teams subsequent to its enactment, and 0 otherwise. We then regress ROA on this interaction term alongside the control variables employed in the main tests.

We specify the following model.

$$ROA_{i,t} = \beta_0 Treat_i * Post_{t-1} + \beta_1 Control_{i,t-1} + \gamma_{t-1} + \epsilon_i + \varepsilon_{i,t-1} \quad (2)$$

As shown in Table-8, the coefficient of *Treat*Post* is positive and significant at the 1% level, after control the bank-level and macro-economic-level variables, the results remain. Therefore, the result further confirms our main finding that digital expertise exerts positive effects on bank performance.

Table 8. Effects of Digital Expertise on Bank Performance – DID

	(1)	(2)	(3)	(4)
VARIABLES	*ROA*	*ROA*	*ROA*	*ROA*
*Treat * Post*	0.1283***	0.1159***	0.1159***	0.0556**
	(4.5558)	(4.6829)	(4.6829)	(2.4206)
Size		0.0043	0.0043	-0.1001***
		(0.1072)	(0.1072)	(-3.8304)

Loan		0.0008	0.0008	-0.0050***
		(0.4450)	(0.4450)	(-3.3612)
Lev		-0.0084	-0.0084	-0.0167***
		(-1.3966)	(-1.3966)	(-2.6212)
Depo		0.0036**	0.0036**	0.0031**
		(2.5821)	(2.5821)	(2.0389)
Npl		-0.1003***	-0.1003***	-0.1097***
		(-11.1029)	(-11.1029)	(-12.3257)
All Num		0.0008	0.0008	-0.0012
		(0.4336)	(0.4336)	(-0.5308)
GDP			0.0000	0.0058***
			(.)	(5.3685)
M2			0.0000	0.0258***
			(.)	(8.6848)
CPI			0.0000	1.5671***
			(.)	(6.1904)
Constant	0.8514***	1.3753	1.3753	4.7712***
	(177.1031)	(1.1181)	(1.1181)	(5.0147)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No
Adjusted R2	0.612	0.669	0.669	0.624
Observations	3,585	3,585	3,585	3,585

4.3.2 Instrument variable

The "New Infrastructure" initiative was first proposed at the 2018 Central Economic Work Conference and formally institutionalized in China's 14th Five-Year Plan (2021-2025) as a core component of the national digital economy governance framework. In the context of this, digital infrastructure is expanding rapidly.

The density of mobile phone base stations (BS) reflects the level of digital infrastructure in a region (such as mobile network coverage and the popularity of communication technology). Areas with high density of BS (such as first-tier cities or technology centers) are often the gathering places for digital technology talents, enabling financial institutions in these hubs to assemble leadership teams. Regions with denser mobile towers typically exhibit stronger digital ecosystems, attracting tech firms, educational institutions, and skilled professionals. This creates a localized talent pool of individuals with digital expertise, increasing the likelihood that banks in such regions recruit executives with technical competencies to navigate digital transformation. The underlying assumption for the relevance condition is that firms located in areas with a higher supply of scream of the crop with digital expertise will be more likely to appoint an executive with digital expertise.

In addition, mobile phone tower density reflects regional disparities in digital infrastructure, which are largely shaped by government-led initiatives and geographic constraints. These factors ensure that mobile tower distribution is exogenous to individual banks' performance, as infrastructure planning is driven by macroeconomic or policy goals rather than bank-specific characteristics, which satisfies the externality assumption.

We thus utilize BS density as an instrumental variable to disentangle the impacts of digital expertise. The first-stage regression results presented in Column 1 of Table-9 indicate the anticipated positive and statistically significant impact of BS on ROA, confirming that the relevance condition for our instrument is met. The second-stage regressions, reported in Column 2 of Table-9, involve regressing bank performance metrics on the instrumented variable and control variables. T-statistics are calculated using bootstrapped standard errors to alleviate bias arising from measurement errors in the estimated independent variables. The coefficient is positive and statistically significant, which is consistent with our hypothesis.

Table 9. Effects of Digital Expertise on Bank Performance – Instrumental Variable (IV)

	(1)	(2)
	First	Second
VARIABLES	*BS*	*ROA*
Dig All	0.056***	

	(4.396)	
BS		0.193***
		(2.590)
Size	0.112	0.009
	(1.240)	(0.282)
Loan	-0.008**	0.004***
	(-2.452)	(3.482)
Lev	-0.025*	-0.006
	(-1.902)	(-1.255)
Depo	0.000	0.003***
	(0.091)	(2.905)
Npl	0.013	-0.112***
	(0.749)	(-19.199)
All Num	-0.004	-0.001
	(-0.697)	(-0.334)
Constant	11.102***	-1.448
	(4.006)	(-1.195)
Bank FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R2	0.931	0.637
Observations	3,040	3,040

4.4 Channel Analysis

We further explore through which channels the digital expertise develop the bank performance. As hypothesized, we expect that digital expertise can facilitate patent-driven technological commercialization by institutionalizing R&D processes, empower managers to deploy machine learning-enhanced credit assessment systems, thereby expanding loan-to-deposit ratios through granular risk detection and implement precision governance frameworks that liberate underutilized capital for strategic reallocation into high-yield assets. These mechanisms collectively enable banks to optimize innovation capacity, risk-adjusted returns, and liquidity management, thereby systematically enhancing overall performance.

4.4.1 Patent channel

In this section, we focus on the top management's attention to the bank's innovation capability. Based on the previous study, we manually collect the number of patents for inventions to measure the bank's innovation capability (*Patent*), which equals the natural logarithm of one plus patent grants.

We propose that the digital expertise create an environment conducive to technological commercialization, directly reinforcing banks' innovation capability to enhance profit margins through proprietary product development. To capture the level of attention to these aspects, we conduct two-stage regress. In column 1-2 of Table-10, we show that the digital expertise is associated with more the number of patents and thus create more profit space. The results imply that digital expertise improve the bank's innovation ability, which they help to enhance the bank's profit performance.

4.4.2 LDR channel

In this section, we focus upon how digital expertise optimizes risk-adjusted returns through loan-to-deposit ratio (LDR) management. Leveraging advances in digital technologies, executives with digital expertise excel at identifying creditworthy borrowers overlooked by traditional methods under China's macroprudential framework while controlling non-performing loans (NPLs) via predictive default modeling. This dual capability generates risk-adjusted yield premiums via enhanced credit allocation efficiency

We also test this channel through two-stage regression analysis. As shown in columns 3-4 of Table-10, digital expertise exhibits a positive association with LDR, and then increases the bank's profit alongside concurrent NPL reduction. These results confirm that digital expertise elevates LDR through NPL mitigation, thereby improving profitability.

4.4.3 Liquidity optimization channel

In this section, we focus on how digital expertise enhances liquidity management efficacy. Since Berger and Bouwman established the measure of liquidity creation, scholars have operationalized this framework across contexts. Duan and Niu use a panel of US banks, find that liquidity creation is associated with higher profitability. This result holds during normal times and the financial crisis. In the digital transformation context, digital leadership enables to optimize real-time reserve allocations through demand forecasting, identify underutilized liquidity pools via transaction pattern analysis and reallocate freed capital into high-yield assets within regulatory constraints with the help of algorithm-driven liquidity management systems.

Similarly, we test this channel through two-stage regression analysis. As shown in columns 5-6 of Table-10, the first-stage results reveal that the digital expertise is associated with the increase of liquidity creation. Then, consistent with Duan and Niu, we observe that heightened liquidity creation drives profitability improvements, The results conclusively demonstrate that digital expertise enhances bank profitability through systematic liquidity creation optimization.

Table 10. Effects of Digital Expertise on Bank Performance – Channel

	(1)	(2)	(3)	(4)	(5)	(6)
	First	Second	First	Second	First	Second
VARIABLES	*Patent*	*ROA*	*LDR*	*ROA*	*LC*	*ROA*
Dig_All	0.055***		0.360***		0.390***	
	(7.869)		(4.567)		(3.178)	
Patent		0.322***				
		(4.471)				
LDR				0.049***		
				(3.559)		
LC						0.046***
						(2.804)
Size	-0.181***	0.056**	2.928***	-0.147***	-2.941***	0.131**
	(-4.713)	(2.248)	(6.782)	(-2.932)	(-4.376)	(2.285)
Loan	0.006***	-0.001	0.924***	-0.044***	-0.316***	0.016***
	(3.794)	(-0.666)	(50.457)	(-3.432)	(-11.081)	(2.970)
Lev	-0.019***	-0.003	-0.264***	0.004	0.342***	-0.025***
	(-3.036)	(-0.787)	(-3.836)	(0.684)	(3.184)	(-3.261)
Depo	-0.004***	0.005***	-0.526***	0.029***	0.393***	-0.015**
	(-2.732)	(4.811)	(-30.147)	(3.915)	(14.469)	(-2.280)
Npl	-0.012	-0.097***	0.064	-0.104***	0.188	-0.109***
	(-1.426)	(-20.522)	(0.702)	(-17.804)	(1.318)	(-13.899)
All_Num	-0.006**	0.002	-0.008	0.001	0.026	-0.001
	(-2.199)	(1.331)	(-0.250)	(0.261)	(0.510)	(-0.386)
Constant	11.075***	-1.444	-1.521	2.196***	51.600**	-0.227
	(9.452)	(-1.400)	(-0.115)	(2.632)	(2.514)	(-0.169)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,585	3,585	3,585	3,585	3,585	3,585
R-squared	0.699	0.641	0.850	0.434	0.545	0.088

5. Conclusion

This paper analyses the impact of managers' digital expertise on bank performance China's rapidly evolving fintech landscape. Prior research on bank performance typically focuses on the managers' demography characters, and does not examine the roles of digital expertise. We also investigate the channels through which various dimensions of managers' characteristics influence banks' risk-taking probability and obtain plausible results. These findings enrich the research on the enhancement of bank performance and may provide insights for the formulation of banks' corporate governance mechanisms.

Leveraging a novel dataset spanning 353 commercial banks over 2008–2022, we reveal that corporate leaders with digital expertise significantly enhance profitability while reducing the bank failure and liquidity risks. Specifically, an increase in Dig All by one standard deviation is associated with an increase in ROA by 8.72%, with subsample analysis indicating that the primary effect stems from board-level leadership, an increase in Dig Board Num by one standard deviation is associated with an increase in ROA by 3.35%. Our heterogeneity analysis further reveals that the impact of managerial digital expertise is more pronounced in state-owned banks, non-publicly listed institutions, and city or rural banks.

Our results are robust to controlling for a comprehensive set of country-level and bank-level determinants. We address endogeneity by employing instrumental variables—specifically, the density of mobile phone base stations—and conducting a difference-in-differences analysis that treats China's Cybersecurity Law as an exogenous shock. Our channel analysis clarifies the pathways by which digital skills work. First, it fosters patent-driven innovation, enabling banks to institutionalize R&D processes and reduce reliance on external fintech vendors. Second, machine learning-enhanced credit assessment optimizes loan-to-deposit ratios (LDR) by expanding credit access to underserved borrowers while curbing non-performing loans (NPLs) through predictive modeling. Third, algorithm-driven liquidity management dynamically reallocates trapped capital into high-yield assets, achieving regulatory compliance without sacrificing profitability. These mechanisms collectively transform digital governance into a strategic lever for balancing innovation and stability.

From a policy standpoint, the results of this study extend upper echelons theory by conceptualizing digital expertise as a critical cognitive dimension in the fintech era and suggest that regulators should prioritize “digital infrastructure equalization” to narrow regional disparities and incentivize talent redistribution, particularly in underserved city or rural banks. For banks, embedding digital literacy in board appointments—especially within risk and innovation committees—emerges as a governance imperative.

References

[1] Yu S, Zheng X, Liu M J., 2025. Board digital expertise and digital innovation: Evidence from commercial banks in China. Research in International Business and Finance, 76: 102854.
[2] Berger, A.N., Bouwman, C.H.S., 2013. How does capital affect bank performance during financial crises? Journal of Financial Economics 109 (1), 146–176.
[3] Berger, A.N., Li, X., Morris, C.S., et al., 2021. The effects of cultural values on bank failures around the world. Journal of Financial and Quantitative Analysis 56 (3), 945–993.
[4] Berger, A.N., Guedhami, O., Kim, H.H., et al., 2022. Economic policy uncertainty and bank liquidity hoarding. Journal of Financial Intermediation 49, 100893.
[5] Conyon, M.J., Haß, L.H., Vergauwe, S., et al., 2019. Foreign experience and CEO compensation. Journal of Corporate Finance 57, 102–121.
[6] Krishnan, J., Wen, Y., Zhao, W., 2011. Legal expertise on corporate audit committees and financial reporting quality. The Accounting Review 86 (6), 2099–2130.
[7] Burkhard, B., Sirén, C., van Essen, M., et al., 2023. Nothing ventured, nothing gained: A meta-analysis of CEO overconfidence, strategic risk taking, and performance. Journal of Management 49 (8), 2629–2666.
[8] Chen, S.S., Chen, Y.S., Kang, J.K., et al., 2020. Board structure, director expertise, and advisory role of outside directors. Journal of Financial Economics 138 (2), 483–503.
[9] Duan, Y., El Ghoul, S., Guedhami, O., et al., 2021. Bank systemic risk around COVID-19: A cross-country analysis. Journal of Banking & Finance 133, 106299.
[10] Hoechle, D., Ruenzi, S., Schaub, N., et al., 2018. Financial advice and bank profits. The Review of Financial Studies 31 (11), 4447–4492.
[11] Wang, C., Xie, F., Zhu, M., 2015. Industry expertise of independent directors and board monitoring. Journal of Financial and Quantitative Analysis 50 (5), 929–962.
[12] Boone, C., Hendriks, W., 2009. Top management team diversity and firm performance: Moderators of functional-background and locus-of-control diversity. Management Science 55 (2), 165–180.
[13] Saghi-Zedek, N., 2016. Product diversification and bank performance: Does ownership structure matter? Journal of Banking & Finance 71, 154–167.

