

# ***The Impact of Digital Transformation Level on the Profitability of Commercial Banks: Evidence from Chinese A Share Listed Banks***

**Yixuan Wu**

*Faculty of Science, The University of British Columbia, Vancouver, Canada  
yixuanwu075@gmail.com*

**Abstract.** The current research collects yearly observation data of China's A-share listed commercial banking institutions covering the 2016–2025 timeframe. A quantitative indicator reflecting banks' digital construction depth is constructed based on word frequency statistics of technology-focused keywords extracted from each sample firm's annual disclosure documents. The indicator of return on equity (ROE) is selected to quantify the profit-making capacity of commercial banks. This paper intends to verify the intrinsic correlation between digital construction depth and profit performance of banking entities. Besides baseline regression, the research sets up an interactive item associated with asset scale and implements grouped empirical tests for banks with different institutional classifications. Empirical outputs demonstrate that the advancement of digital construction presents a positive correlation with sample banks' ROE values. Asset scale acts as a regulating variable within such correlation, and the profit-boosting function brought by digital upgrading appears more salient among banking institutions with smaller asset volumes. The grouped regression results further illustrate that digital construction can significantly lift operating performance for joint-stock commercial banks, whereas such statistically noticeable influence cannot be observed within other banking subgroups. Such empirical evidence proves that digital transformation generates differentiated operating impacts on various banks, whose heterogeneity originates from asset scale differences, resource endowment gaps and institutional property distinctions. The analytical conclusions drawn from this paper can deliver practical empirical references for domestic commercial banks to design customized digital upgrading roadmaps.

**Keywords:** Commercial Bank Profitability, Digital Transformation Level, ROE, Heterogeneity Analysis

## **1. Introduction**

### **1.1. Research background and motivation**

In recent years, the ongoing progress made in digital technologies and information and communication technologies (ICT) has emerged as a fairly important factor that drives economic

growth [1]. Against this backdrop, digital transformation has gradually become a common trend that is observable among financial institutions. When digital technologies are brought into the financial sector, they play a considerable role in promoting the development of financial services, because these technologies make it possible for financial services to go beyond geographical barriers and thus reach a broader range of users, and customers who live in different regions can now complete many banking activities through online channels [2]. In addition, many traditional financial services used to demand a large amount of paper documentation as well as lengthy manual review procedures in the past, but the adoption of digital systems has moved these procedures online, which has cut down the processing time by a notable margin. From a security perspective, digital systems have also strengthened the financial sector's capacity to detect potential risks, since these systems are able to monitor transactions in real time, and as a result they can identify fraudulent activities and irregular transactions more quickly and with greater accuracy [3, 4].

At the same time, third-party payment platforms have grown at a very fast pace, and this growth has brought new challenges to the profitability and market competitiveness of traditional commercial banks. In everyday life, third-party payment platforms are able to offer transfer services that are simple, fast, and free of charge, and they also cover a wide variety of payment scenarios. In contrast, traditional commercial banks tend to involve more complicated procedures, they usually take longer to process transactions, and their main services are relatively basic ones like deposits, transfers, and bill payments. As a consequence, many customers no longer keep their idle funds in bank accounts for daily transactions, but instead they choose to hold their money in third-party payment accounts so that they can use it for consumption and transfers. In the lending market, conventional bank loan applications generally require customers to visit physical branches in person, submit various supporting documents, and wait through a relatively long approval process. Internet finance platforms, by comparison, are able to assess users on the basis of their transaction records and complete loan applications online through simplified procedures, and this adds further competitive pressure to the traditional lending business of commercial banks [5, 6].

Given these challenges, commercial banks have quickened their pace of digital transformation, because they want to maintain and strengthen their competitive standing in the market. By making use of digital technologies, banks are expected to raise their operational efficiency, bring down their operating costs, improve the overall customer experience, and become better adapted to the fast-changing digital economy [7-9]. For these reasons, the question of how digital transformation affects commercial banks' profitability has become a topic that attracts growing attention in both academic research and practical discussions.

## 1.2. Literature review

A fairly large body of research has already looked into how fintech influences the performance of commercial banks. Some previous studies have reported that digitalization contributes positively to bank performance, whereas others hold the view that the rise of internet finance has had an adverse impact on the profitability of China's banking sector. However, a number of existing studies rely on the Peking University Digital Financial Inclusion Index or other indicators at the regional level, and these indicators mainly reflect the external financial environment rather than the effect that a bank's own level of digital transformation has on its profitability [9, 10]. In addition, earlier research has indicated that the positive impact of digitalization tends to be more pronounced among smaller banks, but these studies only divide banks into large and small groups, and this classification approach is relatively simple [11]. Building on the foundations laid by previous studies, the current paper constructs a proxy measure that is based on the text of banks' annual reports, using the

frequency with which digitalization-related keywords occur. It also treats bank size as a continuous variable and includes an interaction term in the regression model, with the aim of investigating more carefully how the effect of digital transformation varies as bank size changes.

### 1.3. Research content and significance

Following the discussion presented above, this study takes Chinese listed commercial banks as its research sample. It builds a proxy variable for the digital transformation level on the basis of how frequently keywords such as "digital transformation," "financial technology," "big data," and "artificial intelligence" appear in bank annual reports, and it uses return on equity (ROE) to represent bank profitability. This research incorporates multiple control variables including bank asset scale, non-performing loan ratio (NPL), capital adequacy ratio (CAR) and loan-to-deposit ratio (LDR), then adopts the multiple linear regression framework to analyze how digital transformation extent correlates with profit performance of commercial banking institutions. In addition, distinct gaps exist among banking players in asset volume, customer resource coverage, technological expenditure input and digital construction progress. On this account, the paper supplements grouped heterogeneity tests to check whether the profit-promoting effect brought by digital upgrading displays disparities among banks of varied categories.

This research has two marginal contributions to existing relevant literature. Firstly, different from prior studies that divide samples into discrete groups according to bank scale, this paper constructs an interaction term between bank asset scale and digital transformation level, and regards bank scale as a continuous variable to systematically explore its moderating influence on the nexus between digital transformation and bank profitability. Secondly, the research classifies sample banks into four categories for grouped regression analysis. By comparing the empirical results of different bank samples, this paper examines the differentiated impacts of digital transformation on banks with distinct ownership attributes, operational modes and technical foundation conditions.

The research conclusions of this paper provide a novel analytical perspective for explaining the heterogeneous effects of digital transformation across commercial banks with different scales and types. Meanwhile, the empirical findings can offer practical empirical references for domestic commercial banks to formulate differentiated development strategies and steadily advance digital upgrading and transformation in the future.

## 2. Methodology

### 2.1. Data source

The sample consists of Chinese A-share listed commercial banks, including Large State-owned Commercial Banks (LSCBs), Joint-Stock Commercial Banks (JSCBs), City Commercial Banks (CCBs), and Rural Commercial Banks (RCBs). The research period is from 2016 to 2025, with data obtained mainly from annual reports and financial information provided by the Choice Financial Terminal (see Table 1).

Table 1. Sample of commercial banks

| Bank Type | Bank Name                                                                                                                                                         |
|-----------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| LSCBs     | Agricultural Bank of China, Bank of Communications, Industrial and Commercial Bank of China, Postal Savings Bank of China, China Construction Bank, Bank of China |

Table 1. (continued)

|       |                                                                                                                                                                                                                                                                                          |
|-------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| JSCBs | Ping An Bank, SPD Bank, China CITIC Bank, China Everbright Bank, Hua Xia Bank, China Minsheng Bank, China Merchants Bank, Industrial Bank, China Zheshang Bank                                                                                                                           |
| CCBs  | Bank of Beijing, Bank of Shanghai, Bank of Jiangsu, Bank of Nanjing, Bank of Ningbo, Bank of Hangzhou, Bank of Guiyang, Bank of Chengdu, Bank of Zhengzhou, Bank of Changsha, Bank of Chongqing, Bank of Qingdao, Bank of Suzhou, Bank of Xi'an, Xiamen Bank, Bank of Lanzhou, Qilu Bank |
| RCBs  | Shanghai Rural Commercial Bank, Chongqing Rural Commercial Bank, Qingdao Rural Commercial Bank, Bank of Changshu, Zhangjiagang Rural Commercial Bank, Bank of Wuxi, Jiangyin Rural Commercial Bank, Suzhou Rural Commercial Bank, Ruifeng Bank, Zijin Bank                               |

## 2.2. Variable selection

### 2.2.1. Dependent variable

ROE is adopted in this study as the main indicator for measuring commercial bank profitability. ROE is generally understood as the ratio of net profit to shareholders' equity, and it reflects how efficiently a bank generates earnings from the capital that shareholders have invested. This indicator is widely regarded as an important measure of bank profitability and shareholder returns [12].

### 2.2.2. Independent variable

The digital transformation indicator is constructed from the frequency of digital-related keywords appearing in banks' annual reports. Earlier studies have demonstrated that the frequency of keywords in texts can be quantified and then used as a research variable [5]. The keyword list is first developed on the basis of digital technology terms that have been widely adopted in previous research, including "artificial intelligence", "big data", "cloud computing" and "blockchain" [13]. It also adds application-related keywords that are connected to the business activities of commercial banks, such as "mobile banking", "intelligent risk management", "online loans" and "intelligent customer service", so as to provide a more comprehensive measure of digital-related disclosures in annual reports.

Because the length of annual reports differs from one bank to another, using only the total number of keyword occurrences might be affected by the length of the reports. Therefore, this study divides the total number of digital-related keyword occurrences by the total word count of each annual report to construct the digital transformation indicator:

$$DigitalText_{it} = \frac{A}{a} \quad (1)$$

Where  $A$  represents the total number of digital-related keyword occurrences, and  $a$  denotes the total word count of the corresponding annual report.

### 2.2.3. Control variables

Drawing on previous studies and taking into consideration the sample size and data availability, this study includes bank size (Size), the non-performing loan ratio (NPL), the capital adequacy ratio (CAR), and the loan-to-deposit ratio (LDR) as control variables [14, 15].

Bank size (Size) is proxied by the natural logarithm of total assets, and it reflects differences in the scale of commercial banks. Bank size may influence profitability through differences in customer base, business coverage, and available resources. The non-performing loan ratio (NPL) serves as an indicator of asset quality and credit risk, and a higher NPL usually suggests a greater risk of loan losses, which may reduce bank profitability. The capital adequacy ratio (CAR) measures the financial strength of a bank, and the level of capital may affect a bank's capacity to bear risks and keep its operations stable. The loan-to-deposit ratio (LDR) reflects the relationship between loans and deposits, and it indicates the intensity of lending activities while also being related to a bank's liquidity risk.

### 2.3. Model specification

This study estimates the following baseline regression model:

$$ROE_{it} = \beta_0 + \beta_1 \log\_Digital_{it} + \beta_2 size_{it} + \beta_3 NPL_{it} + \beta_4 CAR_{it} + \beta_5 LDR_{it} + \mu_i + \lambda_t + \epsilon_{it} \quad (2)$$

Where  $i$  and  $t$  denote the bank and year, respectively. ROE is return on equity,  $\log\_Digital$  is the logarithm of the digital keyword frequency index, Size represents bank size, NPL is the non-performing loan ratio, CAR is the capital adequacy ratio, and LDR is the loan-to-deposit ratio.  $\beta_0$  is the intercept,  $\beta_1$  measures the effect of the digital transformation level on bank profitability, and  $\beta_2$  to  $\beta_5$  represent the effects of the control variables.  $\mu_i$  stands for bank fixed effects,  $\lambda_t$  stands for year fixed effects, and  $\epsilon_{it}$  is the error term.

Previous research has found that digital transformation may generate greater benefits for smaller banks [11]. Building on these findings, this study further incorporates an interaction term between the digital keyword frequency index and bank size to investigate whether bank size influences the impact of digital transformation on profitability. The following model is estimated:

$$ROE_{it} = \beta_0 + \beta_1 \log\_Digital_{it} + \beta_2 size_{it} + \beta_3 (\log\_Digital_{it} \times size_{it}) + \beta_4 NPL_{it} + \beta_5 CAR_{it} + \beta_6 LDR_{it} + \mu_i + \lambda_t + \epsilon_{it} \quad (3)$$

### 3. Descriptive statistics

Table 2 lists the descriptive statistical indicators of all variables adopted within this empirical study. Standardized data screening and preprocessing procedures yield 362 effective sample observations in the final dataset. The Digital indicator records an average value of 0.000272 alongside a standard deviation of 0.000218, and its numerical range stretches from 0 up to 0.00287. This variable quantifies the share of digital technology keywords against the full word count disclosed in each bank's annual report, which explains the generally low magnitude of its numerical readings. In addition, the maximum value of Digital is considerably higher than its mean, and the standard deviation is relatively large when compared with the mean, which shows that the digital transformation level varies quite a lot across banks and years, and it displays a certain degree of right skewness. For this reason, this study transforms the variable using Equation (4) to reduce the influence of extreme values and to avoid the problem that arises from taking the logarithm of zero.

$$\log\_Digital = \ln(1 + Digital \times 10000) \quad (4)$$

For ROE, the average value is 10.5 and the standard deviation is 2.59, which suggests that the sample banks have a reasonable level of shareholder returns while differences still exist across banks. NPL has an average of 1.31 and a standard deviation of 0.351, indicating that the overall non-performing loan level is relatively low. CAR has an average value of 14.1, and its standard deviation of 1.66 indicates that the sample banks generally maintain a high level of capital adequacy with relatively small differences among them. The mean value of LDR is 81.4, with a range from 48.1 to 110, suggesting that there are considerable differences in lending intensity across banks.

Table 2. Descriptive statistics

| Variable            | N   | Mean     | SD       | Min  | Max     |
|---------------------|-----|----------|----------|------|---------|
| <i>ROE</i>          | 362 | 10.5     | 2.59     | 3.46 | 17.7    |
| <i>Digital</i>      | 362 | 0.000272 | 0.000218 | 0    | 0.00287 |
| <i>log\_Digital</i> | 362 | 3.72     | 3.18     | 1    | 29.7    |
| <i>Size</i>         | 362 | 28.2     | 1.66     | 25.1 | 31.6    |
| <i>NPL</i>          | 362 | 1.31     | 0.351    | 0.66 | 2.47    |
| <i>CAR</i>          | 362 | 14.1     | 1.66     | 10.8 | 19.7    |
| <i>LDR</i>          | 362 | 81.4     | 12.6     | 48.1 | 110     |

Table 3 shows the correlation matrix between *log\\_Digital* and the control variables. The correlation coefficient between *log\\_Digital* and *Size* is 0.542, which points to a moderate positive association between bank size and digital transformation level. The correlation coefficients among the remaining variables are relatively low, and this suggests that there are no strong correlations among them.

Table 3. Correlation matrix

|                     | <i>log\_Digital</i> | <i>Size</i> | <i>NPL</i> | <i>CAR</i> | <i>LDR</i> |
|---------------------|---------------------|-------------|------------|------------|------------|
| <i>log\_Digital</i> | 1.000               | 0.542       | -0.215     | 0.228      | 0.301      |
| <i>Size</i>         | 0.542               | 1.000       | 0.085      | 0.314      | 0.247      |
| <i>NPL</i>          | -0.215              | 0.085       | 1.000      | -0.172     | 0.109      |
| <i>CAR</i>          | 0.228               | 0.314       | -0.172     | 1.000      | -0.112     |
| <i>LDR</i>          | 0.301               | 0.247       | 0.109      | -0.112     | 1.000      |

To further test whether these correlations might lead to multicollinearity, this study performs a VIF test. Table 4 shows that all VIF values are below 2, which indicates that multicollinearity is unlikely to be a serious concern in the regression analysis.

Table 4. VIF test results

| Variable           | VIF   |
|--------------------|-------|
| <i>log_Digital</i> | 1.676 |
| <i>Size</i>        | 1.652 |
| <i>NPL</i>         | 1.180 |
| <i>CAR</i>         | 1.208 |
| <i>LDR</i>         | 1.191 |

## 4. Results

### 4.1. Baseline regression results

Table 5 presents the baseline regression results. The coefficient of *log\_Digital* is 0.6246 and is significant at the 5% level. This demonstrates that, after controlling for bank size, asset quality, capital adequacy, the loan to deposit ratio, as well as bank and year fixed effects, the digital transformation is positively related to the ROE of commercial banks. Specifically, a one unit increase in *log\_Digital* is associated with an average increase of 0.6246 units in ROE.

Table 5. Baseline regression results

| Variable           | ROE                       |
|--------------------|---------------------------|
| Intercept          | -103.4000***<br>(19.5200) |
| <i>log_Digital</i> | 0.6246**<br>(0.2479)      |
| <i>Size</i>        | 4.5160***<br>(0.6902)     |
| <i>NPL</i>         | -3.2490***<br>(0.3843)    |
| <i>CAR</i>         | -0.4446***<br>(0.0752)    |
| <i>LDR</i>         | -0.0051<br>(0.0125)       |

Table 5. (continued)

|                              |       |
|------------------------------|-------|
| Bank Fixed Effects (Bank FE) | YES   |
| Year Fixed Effects (Year FE) | YES   |
| N                            | 362   |
| R <sup>2</sup>               | 0.823 |

Note: \*\* and \*\*\* denote significance at the 5% and 1% levels, respectively. Standard errors are shown in parentheses.

## 4.2. Interaction effect

Table 6 reports the regression results after the interaction term  $\log\_Digital \times Size$  is included. The coefficient of this interaction term is -0.3416, and it is significant at the 5% level. This result suggests that the positive effect of digital transformation on ROE becomes weaker as bank size increases, and by contrast, digital transformation has a stronger profitability effect for banks that are relatively smaller.

Table 6. Results of the bank size moderation analysis

| Variable                         | ROE                    |
|----------------------------------|------------------------|
| <i>log_Digital</i>               | 10.4500***<br>(3.0330) |
| <i>Size</i>                      | 4.6930***<br>(0.6819)  |
| <i>NPL</i>                       | -2.9750***<br>(0.3877) |
| <i>CAR</i>                       | -0.3859***<br>(0.0762) |
| <i>LDR</i>                       | -0.0071<br>(0.0123)    |
| <i>log Digital</i> × <i>size</i> | -0.3416**<br>(0.1051)  |
| Bank FE                          | YES                    |
| Year FE                          | YES                    |
| N                                | 362                    |

Table 6. (continued)

| $R^2$ | 0.8289 |
|-------|--------|
|-------|--------|

Note: \*\* and \*\*\* denote significance at the 5% and 1% levels, respectively. Standard errors are shown in parentheses.

### 4.3. Heterogeneity analysis

On the basis of the classification of Chinese A-share listed commercial banks provided by the Choice Financial Terminal, this study divides the sample into four groups: LSCBs, JSCBs, CCBs, and RCBs, and then separate regressions are run for each group.

Table 7 presents the heterogeneity regression results. The coefficient of *log\_Digital* is statistically significant at the 5% level only for JSCBs, with a coefficient of 1.51231, while the coefficients for the other three types of banks are not statistically significant.

Table 7. Heterogeneity regression results by bank type

| Variable           | (1)<br>LSCBs               | (2)<br>JSCBs             | (3)<br>CCBs              | (4)<br>RCBs              |
|--------------------|----------------------------|--------------------------|--------------------------|--------------------------|
| Intercept          | -15.972203<br>(11.075430)  | 3.24982<br>(14.00856)    | 11.93486<br>(7.84552)    | 10.56690<br>(8.55609)    |
| <i>log_Digital</i> | 0.273599<br>(0.270851)     | 1.51231*<br>(0.57750)    | -0.71384<br>(0.48713)    | 0.45608<br>(0.54475)     |
| <i>Size</i>        | 1.046049*<br>(0.407292)    | 0.57442<br>(0.50437)     | 0.47112<br>(0.24756)     | 0.17992<br>(0.28983)     |
| <i>NPL</i>         | 0.769232<br>(0.524821)     | -3.23876***<br>(0.91913) | -5.36641***<br>(0.52734) | -3.50138***<br>(0.42858) |
| <i>CAR</i>         | -0.063764<br>(0.136277)    | -0.44028**<br>(0.15515)  | 0.07019<br>(0.16653)     | -0.11601<br>(0.12146)    |
| <i>LDR</i>         | -0.040403***<br>(0.009708) | 0.04904*<br>(0.02275)    | -0.07897***<br>(0.01591) | 0.04157<br>(0.02701)     |
| Bank FE            | NO                         | NO                       | NO                       | NO                       |
| Year FE            | YES                        | YES                      | YES                      | YES                      |
| N                  | 55                         | 87                       | 137                      | 83                       |
| $R^2$              | 0.9114                     | 0.7712                   | 0.6831                   | 0.5414                   |

Note: \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are shown in parentheses.

## 5. Discussion

The baseline regression results indicate that digital transformation is positively correlated with the ROE of commercial banks. A possible explanation is that online services enhance the convenience of customer transactions, which helps improve customer experience and strengthen customers'

willingness to use banking services in the long term. Banks can also combine customers' transaction records and usage patterns to more accurately identify the needs of different customers and provide more targeted products and services. This may help improve customer retention rates and the promotion efficiency of financial products, thereby supporting bank revenue growth. On the other hand, as more basic business operations are shifted to online channels, banks' reliance on physical branches and counter services decreases, potentially leading to reduced operational costs such as rent, labor, and daily management. The improvement in revenue and cost savings jointly enhance the efficiency of banks' utilization of shareholder capital, which may ultimately manifest as higher ROE.

The results of the interaction analysis further indicate that digital transformation has a more significant impact on the profitability of banks with relatively smaller scales. One possible reason is that banks with smaller scales typically have flatter hierarchies and simpler organizational structures, allowing digital tools to be quickly disseminated across various departments with relatively lower implementation costs, thereby enhancing their operational efficiency more easily. Furthermore, the existing information systems and digital foundations of such banks often have considerable room for improvement, making digital investments potentially lead to more pronounced marginal benefits. In contrast, larger banks have a larger number of departments and more complex business systems, and the implementation of digital projects often requires coordination across multiple systems and management levels, which may delay the process of transforming digital investments into profit improvements.

The heterogeneity analysis shows that JSCBs is the only kind of banks that have significant positive relationship between digitalization and ROE. The root cause of this result might be the difference between the organizational structure, operational model, and market competition environment of banks. LSCBs always have sufficient asset size and resource endowment and may already have a solid foundation in digitalization. The newly increased digital investment is more reflected in the updating and improvement of existing systems, rather than significant changes to the original business model, so the marginal benefits it brings may be relatively limited. CCBs and RCBs may face certain limitations in terms of technical talent, system construction, and sustained investment capabilities, so it usually takes longer for digital construction to generate stable returns from investment [15]. In contrast, JSCBs face strong market competition, place more emphasis on operational efficiency, customer service, and product innovation, and have relatively sufficient financial and technological conditions, making it easier to transform digital construction into actual business growth and profit improvement.

Overall analysis suggests the profit value of digital construction cannot be judged solely by bank asset volume. To fully interpret its heterogeneous effects on financial performance, researchers need to integrate multi-dimensional constraints covering technical foundation, capital endowment and professional talent reserves for comprehensive evaluation.

## 6. Conclusion

This paper selects a decade-long balanced panel dataset covering all China-listed commercial banking institutions to conduct empirical tests, with multivariate linear regression serving as the core analytical tool to unpack the linkage between digital construction depth and banks' overall financial operating results. Model estimation outputs indicate that deepened digital development brings statistically meaningful growth to sample banks' ROE. This quantitative rule implies institutions with higher digitalization level tend to secure stronger profit levels. Additional tests built on cross-variable interaction terms confirm that tech-driven profit growth works more remarkably for banks with limited asset volume. Separate regressions split by institutional categories also

capture obvious outcome gaps across various bank forms: digital transformation generates statistically significant profit growth solely for JSCBs, whereas no significant effect is found for LSCBs, CCBs, and RCBs.

The above empirical discoveries deliver targeted planning references for banking entities to design customized digital development roadmaps matching their inherent resource endowments and operational traits. LSCBs possess complete business frameworks, stable client groups and well-established digital foundations, so their subsequent tech layout ought to shift focus away from blind capital expansion on digital hardware and software. Therefore, the operators will advance their refined digital management and boost the efficiency of resource use to generate extra income. JSCBs face intense competition in the market and have flexible resource allocation mechanisms; they should continue to leverage the strengths of this system fully to expand profits through digital infrastructure. CCBs and RCBs cannot replicate the digital development path of large state-owned or joint-stock enterprises mechanically. Regional banking operators should align technology input arrangements with local operating strengths, concentrate limited digital budgets on core local service modules such as resident client services, micro and small enterprise lending, community financial businesses and risk monitoring systems, and thus raise the actual output efficiency of each unit of digital capital input.

This study is not without fault. First, it builds a proxy variable for digital transformation based on the frequency of digital-related keywords in banks' annual reports, and this method may be affected by disclosure practices and textual expressions in the annual reports; thus, it may not fully reflect the actual level of banks' digitalisation. Second, in the heterogeneity test, several groups of listed commercial banks are used to carry out group-specific regressions. However, some of these bank groups have relatively small sample sizes, which may affect the stability and interpretability of the regression results. ROE is used to gauge the profitability of banks in this study, although there is an overall trend of an increase or decrease in profitability, it is unclear whether the causes are due to higher non-interest income, a lower cost-to-income ratio, or more effective risk management, etc.

In the future, some research can add more direct digital indicators, such as IT investment, the proportion of online business, and the number of mobile banking or app users, to better reflect the actual degree of digitalisation of banks. Variables that indicate the intermediary path can also be included to determine whether digitalisation affects bank profitability through channels such as non-interest income, cost-to-income ratio and risk-adjusted return on capital. In the future, a larger sample size and the application of mixed-effects models can be used to account for individual differences in banks and changes over time more effectively. Given the above optimisations, the following research can delve into more specific details of the mechanisms and paths through which digitalisation by commercial banks affects profitability.

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