Study on the Impact of Digital Economics on Regional Credit Risk of Commercial Banks

Linjing Qu
719495901@qq.com

School of International Education, Wuhan University of Technology, Hubei, 430070 Wuhan, China

Abstract: In recent years, digital economics has been a vital strength in element resource reconstruction and economic structure remodeling, bringing changes for modern commercial banks and potentially impacting commercial banks' credit risk control. Based on panel data from 30 Chinese provinces and cities from 2011-2019, we measured the development level of digital economics in different provinces and cities and formed data sets with factor analysis. A fixed effect model was used to perform a benchmark regression analysis and examine the impact of digital economics on non-performing loan ratio in theoretical and empirical dimensions. The result show that the development of digital economics has marked a negative impact on non-performing loan ratio of commercial banks.

Keywords: digital economics; commercial bank; non-performing loan ratio; credit risk

1 Introduction

In recent years, China's digital economics has been developing rapidly and its scale has ranked top two over the world. According to *China Internet Development Report 2021* issued on 26th September, 2021, the scale of China's digital economics has reached 39.2 trillion yuan in 2020, accounting for 38.6% of China's GDP, and maintaining a high growth rate of 9.7%. And with big data, cloud computing, AI, and blockchain gradually being applied to finance, the depth and breadth of commercial banks' digital transformation have been improved. The fourteenth Five-year Plan has clearly stated that "we should accelerate the digital development." Currently, more than 75% of commercial banks in China have developed digital transformation proposals. Commercial banks, as an important role in the reform of digital economics, can also exert certain influence on the management and control of non-performing loans.

There is no unified definition of digital economics. In view of previous studies (Guo et al., 2016; Wang, 2019; Han et al., 2019) [1][2][3], digital economics is the sum of economic activities based on the Internet and related emerging technologies (such as mobile Internet, big data, cloud computing, AI, etc.). It not only includes e-commerce and Internet finance, but also digital transformation in traditional industries. China's financial systems are very different from that of developed and mature economies. The capital market in China is still at an initial development stage, and banks still dominate the financial systems and play a significant role in the allocation of financial assets (Zhu et al., 2012) [4]. The development of digital economics has brought opportunities and challenges to the development of commercial banks in various fields. How digital economics will change commercial banks has aroused academic attention. In terms of loans, Yi et al. (2019) [5] considered that digital economics can improve transactional efficiency

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by identifying credit relationship through technology, taking network platforms as an organization. Dai et al. (2014) [6] believed that digital economics has boosted financial development but increased capital costs and reduced profitability. As for finance, Qiu et al. (2018) [7] argued that the development of digital economics has changed the asset and liability structure of commercial banks, thus increasing the risk-taking behavior. In terms of operation, Wang et al. (2021) [8] argued that traditional capabilities, business logic and operating models are often difficult to directly match the digital economics mode. In fact, the above-mentioned research has discussed multifaceted impact of digital economics on finance, but there is little literature on the relationship between digital economics and non-performing loan ratio, which is an important factor causing systemic financial risk (Zhang et al., 2014) [9]. Therefore, the study of the relationship between digital economics and non-performing loan ratio has practical significance. In this paper, we will analyze the relationship between digital economics and non-performing loan ratio of commercial banks from both theoretical and empirical perspectives.

2 Theoretical Analysis

One of the purposes of risk management in commercial banks is to reduce the non-performing loan ratio to ensure that there is no or less risk in credit assets. As for internal factors of commercial banks, banks' internal managing efficiency and scale have some influence on banks' credit risk: the rising of cost and efficiency and the increase of bank's scale may be led to a decline of bank credit asset quality (Zheng et al., 2020) [10]. Big data and AI technologies have helped manage credit more scientifically. The efficiency and accuracy are improved through information flow tracking. In turn, scientific decisions of bank staff and the effectiveness of management can be improved so that non-performing loan ratio can be controlled effectively. As for external factors of commercial banks, administrative intervention of government and enterprise innovation have a bad impact on non-performing loans. Liu et al., 2017) [11] considered that the Internet of Things technology of digital economics can monitor capital flow, information and commercial activities, and other dimensions of commercial banks in real time, while big data can collate and analyze massive information which is benefit for central financial regulators to grasp the credit situation of commercial banks and carry out corresponding supervision and management actions to achieve credit risk control. Digital economics which takes big data, cloud computing and blockchain as core technologies empower digital, intelligent and Internet transformation of enterprises. It can enhance the profitability and development space of enterprises, thereby improving their repayment capacity and reducing the risk of credit default. In conclusion, we believe that digital economics can help reduce non-performing loan ratio of commercial banks.

3 Research Design

3.1 Data Sources

In this study, we took the panel data of 30 provinces and cities in China mainland (except Tibet) as the research object, which are publicly disclosed in 2011~2019. The actual data of the non-performing loan ratio of China's provincial and municipal commercial banks from 2011 to 2019 come from *China Financial Statistics Yearbook*. Digital economics indicator related data all comes from the *Statistical Report on Internet Development in China* each year, and others come from the National Bureau of Statistics and period local yearbooks. It should be noted that Tibet was excluded from the research due to the lack of related data.

3.2 Selection and Measurement of Variables

3.2.1 Explained Variable: Non-performing Loans Ratio (NPL)

The credit risk in commercial banks is measured by non-performing loans ratio. The higher the non-performing loans ratio, the higher the credit risk that commercial banks have to undertake (Sun et al., 2017; Sun et al., 2013) [14][13]. *Guidelines on Risk-Based Loan Classification* issued in 2001 classified bank loans into five categories: normal loan, special mention loan, substandard loan, doubtful loan and loss loan, where the latter three are collectively referred to non-performing loans. And the proportion of non-performing loans in the total loan balance of commercial banks in the same period is the non-performing loan ratio.

3.2.2 Explanatory Variable: Digital Economics (DE)

a) Definition of Digital Economics

This paper draws on the practices of Han et al. (2019) [3] and Sun et al. (2021) [12] to evaluate the development of the digital economy from two dimensions: Internet infrastructure and Internet information resources, as shown in **Table 1**. Specifically, the average bytes per web page, the number of web pages in each province, the number of bytes in each province's web pages, and the proportion of IPv4 addresses in each province reflect the inter-provincial differences in the abundance of Internet information. In terms of Internet infrastructure, the use of provincial domain names accounts for the total ratio and the number of domain names in each province.

Table 1 Measure index of digital economics

First-level evaluation dimension	Secondary evaluation index	Importance of indicators
Internet information resources	Average bytes per web page	Reflect resource abundance level of province Internet information
	Number of web pages in each province	Represent provincial allocation level of Internet information
	Number of bytes in each province's web pages	Show the abundance of inter-provincial Internet information
	Proportion of IP addresses in the total number of provinces	Describe resource allocation of inter-provincial IP addresses
Internet infrastructure	Proportion of Provincial Domain Names in total	Describe resource allocation of Provincial Domain Names
	Domain Names of every province	Measure development level of Provincial Domain Names

b) Computing Results of Digital Economics

Six second-level evaluation indexes were adopted in **Table 1** to measure digital economics: the average number of bytes per page, number pages by province, number of bytes of web pages in each province, the ratio of IP addresses in each province, the ratio and number of domain names in each province. SPSS (Statistical Product and Service Solutions), a widely used program for statistical analysis, was then used to analyze the dimensionality reduction of each provincial cross-section data index to obtain the comprehensive score of the digital economy in each year. Due to the length limitations, this paper only presented the results of factor processing in 30 provinces and cities in 2019, as shown below:

KMO and Bartlett's Test

Before principal components analysis (PCA), the selected variables should be tested first. The test contains the relative size of simple correlation coefficient and partial correlation coefficient between primitive variables. The calculation formula of KMO statistics is as followed (r is correlation coefficient and β is partial correlation coefficient). The KMO statistics is 0.733, as shown in **Table 2**, which makes the sample data suitable for factor analysis.

$$\mathrm{KMO} = \frac{\Sigma\Sigma_{i\neq j}\mathrm{r}_{ij}^2}{\Sigma\Sigma_{i\neq j}\mathrm{r}_{ij}^2+\Sigma\Sigma_{i\neq j}\beta_{ij}^2} \tag{1}$$

Table 2 KMO and Bartlett's Test

KMO measure of sampling adequacy		0.737
Bartlett's test of sphericity	Approx. Chi-Square	270.256
	Degree of freedom	15
	Significance	0.000

Calculation of Eigenvalue and Variance Contribution

The Eigenvalue and variance contribution of principal component factor by the measures of digital economics are shown in **Table 3**. From the analysis results, the first two Eigenvalues are larger, which are 3.804 and 1.318. The accumulated contribution rate reaches to 85.367% of the first two Eigenvalues, which shows that the vast majority of the information represented by the sample is better explained.

Table 3 Total Variance

Components	Initial Eigenvalue			Extraction Sums of Squared Loading			Sums of Squares of Rotated Loading		
	Total	ANOVA	Cumulative % of Variance	Total	ANOVA	Cumulative % of Variance	Total	ANOVA	Cumulative % of Variance
1	3.804	63.395	63.395	3.804	63.395	63.395	3.359	55.984	55.984
2	1.318	21.971	85.367	1.318	21.971	85.367	1.763	29.382	85.367
3	0.709	11.812	97.178						
4	0.142	2.365	99.544						

5	0.023	0.389	99.932						
6	0.004	0.068	100.000						

Establishment of Factor Loading Matrix

The relationship between the six selected digital economics measurement and evaluation indicators: the average bytes per web page, the number of web pages in each province, the number of bytes in each province's web pages, the proportion of IP addresses in the total number of provinces, the proportion of Provincial Domain Names in total and Domain Names of every province and these two principal component factors form the factor loading matrix, which can explain these two principal component factors. It is found that most factors are related to many variants in research process, and the explanation of initial factors is difficult, so varimax rotation is adopted to transform them. Based on rotated factor loading matrix (**Table 4**), the proportion of principle factor F_1 in average bytes per web page (X_1), the number of web pages in each province (X_3), the number of bytes in each province's web pages (X_5) and the proportion of IP addresses in the total number of provinces (X_6) is larger. The proportion of principle factor F_2 in the loading of Provincial Domain Names in total and Domain Names of every province is large. Therefore, F_1 is the evaluation factor of the Internet sources dimension and F_2 is the factor of the Internet infrastructure dimension.

Table 4 Rotated Component Matrix [a]

	Components	
	1	2
X_1	0.472	0.294
X_2	0.489	0.813
X_3	0.963	0.220
X_4	0.072	0.966
X_5	0.978	0.147
X_6	0.959	0.218

Extraction method: principal components analysis. Rotation method: varimax with Kaiser normalization. a. The rotation has converged after 3 iterations.

Score of Factor Variables

Factor analysis expression can be combined concluded from **Table 5**, the score coefficient of factor components and the specific scores of the two factors of digital economics can be calculated by substituting the raw data into the already combined factor equations.

Table 5 Component Score Coefficient Matrix

	Components	
	1	2
X_1	0.178	-0.013
X_2	-0.004	0.481
X_3	0.306	-0.063
X_4	-0.178	0.648
X_5	0.319	-0.100
X_6	0.304	-0.064

Extraction method: principal components analysis. Rotation method: varimax with Kaiser normalization. Component score.

Based on **Table 5**, the factor analysis expression is as followed:

$$F_1 = 0.178X_1 - 0.004X_2 + 0.306X_3 - 0.178X_4 + 0.319X_5 + 0.304X_6 \quad (2)$$

$$F_2 = -0.013X_1 + 0.481X_2 - 0.063X_3 + 0.648X_4 - 0.1X_5 - 0.064X_6 \quad (3)$$

Synthesis Scores

After getting the specific score of the factors, the synthesis score is obtained by weighted calculation of the principal components, and the variance contribution rates of rotated factors are taken as the weight value of every factor. The synthesis score is as followed:

$$\mathrm{SCORE} = 54.53/(54.53 + 29.975) \times \mathrm{F}_1 + 29.975/(54.53 + 29.975) \times \mathrm{F}_2 \quad (4)$$

Table 6 Main Factors and Total Scores

Province	Total Score	Province	Total Score	Province	Total Score
Beijing	3.11	Zhejiang	0.64	Hainan	-0.4
Tianjin	-0.03	Anhui	-0.32	Chongqing	-0.24
Hebei	0.11	Fujian	0.81	Sichuan	-0.02
Shanxi	0.11	Jiangxi	-0.27	Guizhou	-0.3
Inner Mongolia	-0.54	Shandong	0.07	Yunnan	-0.32
Liaoning	-0.24	Henan	0.31	Shaanxi	-0.36
Jilin	-0.41	Hubei	-0.15	Gansu	-0.48
Heilongjiang	-0.35	Hunan	-0.08	Qinghai	-0.6
Shanghai	0.33	Guangdong	1.53	Ningxia	-0.62
Jiangsu	0.14	Guangxi	-0.31	Xinjiang	-0.57

Control Variables

In view of the previous studies (Sun et al., 2021; Han et al., 2019; Li et al., 2018) [14][3][15], the following variables are selected as control variables in this essay. Due to some of the data are not disclosed, the marketization level of Xinjiang in 2018 and 2019 is replaced by the data from 2017.

Table 7 Definition of Variables

Variables	Name of Variable	Variable Symbol	Index Calculation Method
Explained Variable	Non-performing Loan	NPL	Non-performing Loan of Every Province's Commercial Banks
Explanatory Variable	Digital Economics	DE	Factor Analysis
Control Variables	Marketization Level	MAR	Non-state-owned Enterprise Employees/ Total

			Employment
	Degree of Financial Development	FIN	Sum of Deposit and Loan Balances of Financial Institutions at the End of the Year/GDP
	Industrial Structure	IND	Tertiary Industry Output/ Secondary Industry Output

3.3 Model Construction

Panel data are taken for this study, and three main models are used for panel regression analysis: Pooled OLS, Fixed Effects Model and Random Effects Model. The following model is constructed according to the direct conduction mechanism of digital economics' credit risk.

$$NPL_{it} = \alpha_0 + \alpha_1 DE_{it} + \alpha_2 MAR_{it} + \alpha_3 FIN_{it} + \alpha_3 IND_{it} + \mu_i + \varepsilon_{it} \quad (5)$$

In this regression model, the i represents different provinces, and represents time (year). DE_{it} indicates the comprehensive evaluation score of digital economic indicators in province i in the t year. MAR_{it} shows the marketization level of province i in the t year. FIN_{it} denotes the degree of financial development of province i in the t year. IND_{it} is the output ratio between tertiary industry and secondary industry. The μ_i is province-based fixed effect used to control the impact of inter-provincial individual differences on the regression results. ε_{it} is the random perturbed variable.

4 Analysis of Empirical Results

4.1Descriptive Statistic

To present the characteristics of variables more directly, the variables data are first analyzed descriptively by importing the data into the econometric statistical software Eviews 10.0 and the operations are carried out with the following descriptive statistics.

Table 8 Descriptive Statistic Results of Variables

Variables	Mean	Standard Deviation	Median	Max.	Min.
DE	0.012593	0.763586	-0.24	3.59	-0.66
NPL	1.612444	1.076472	1.3	8.7	0.35
MAR	0.908564	0.04718	0.923753	0.961189	0.379417
FIN	3.168907	1.139328	2.967552	8.131033	1.517521
IND	1.17391	0.666441	0.994956	5.169242	0.518032

From the descriptive statistic results, the median of argument DE (digital economics metric) is 0.012593, the max is 3.59 and the min is -0.66. The median of dependent NPL (non-performing loan) is 1.612444, the max is 8.7 and the min is 0.35. this large difference reflects the high variation in the status and development of non-performing loans between different provinces and cities in the sample. The median of control variable MAR (marketization level) is 0.04718, which reflects a relatively minor difference in inter-provincial marketization level. The max of control variable FIN Financial Development Degree is 8.131033, and its min is 1.517521. This large difference reflects the big variation in the development of inter-provincial financial levels. The mean of control variable IND (industrial structure) is 1.17391, the median is 0.994956. The approximate numbers indicate that the inter-provincial industrial structure is more in line with normal distribution.

4.2 Regression Results of Panel Data Model

The baseline regression is adopted to make control variables add to the model sequentially. The results are shown in **Table 9**. The core explanatory variables digital economics is added in column (1), marketization degree is added in column (2), financial development level is added in column (3), and industrial structure is added in column (4). The regression results of **Table 9** indicate that R^2 is increasing, which reflects the explanation power of explanatory variable is increasing independent. The result shows the coefficient of digital finance is negative. The above results support this essay's research hypothesis that the development of digital finance is beneficial in reducing the non-performing loan ratio of commercial banks.

Table 9 Benchmark Regression Results

Variable	NPL (1)	NPL (2)	NPL (3)	NPL (4)
DE	-0.086101^{***} (-0.273498)	-0.0924^{***} (-0.295101)	-0.067757^{***} (-0.255589)	-0.059749^{***} (-0.233381)
MAR		3.355493^{***} (1.90504)	0.60757^{***} (0.400345)	0.555102^{***} (0.378752)
FIN			1.334854^{**} (9.749305)	0.744354^{**} (3.885099)
IND				1.183642^{**} (4.258787)
Constant				
R^2	0.189348	0.201524	0.430087	0.470761
N	270	270	270	270

Note: The test values *t* is in parentheses; *, ** and, *** indicate that they are significant at 10%, 5%, and 1%, respectively.

5 Conclusions

Based on panel data of 30 Chinese provinces and cities from 2011-2019, we used factor analysis to measure the development level of digital economics in different provinces and cities and form a dataset. We then adopted a fixed effects model to analyze benchmark regression with the data and conducted corresponding descriptive statistics to examine the impact of digital economics on non-performing loan ratio from both theoretical and empirical perspectives. Here are the conclusions drawn according to the research results: the development of digital economics has a significant negative impact on the non-performing loan ratio of commercial banks. Every time the development level of digital economy increases by one unit, the non-performing loan rate can be significantly reduced by 0.060 units, which reflects that the development of digital economy is conducive to reducing the non-performing loan rate.

Based on the findings of this paper, we propose the following suggestions: On the one hand, government or relevant departments should speed up digital transformation, such as strengthening enhancing the bank's banks' networking and smart construction; meanwhile, use digital technologies can also be used to build risk management systems and as well as to optimize the credit control mechanism of commercial banks, and thus achieving high-quality control of credit risks. On the other hand, effective measure shall be taken to enhance the level of digitalization in China's modern industries, which can be served as a good foundation for credit risk management, thereby promoting the integration of the digital economy and the real economy.

References

[1] Guo J T, Luo P L. Does the Internet contribute to total factor productivity in China. Management World. 2016; (10): 34-48.

[2] Wang J. Study on the Digital Economy Drives High-Quality Economic Development: Factors Allocations and Strategic Choices. Social Sciences in Ningxia. 2019; (5): 88-94.

[3] Han X F, Song W F, Li B X. Can the Internet Become a New Momentum to Improve the Efficiency of Regional Innovation in China. China Industrial Economics. 2019; (7): 119-136.

[4] Zhu X R, Rao, P G, Bao M M. Ownership structure, Credit Behavior and Bank Performance - An Empirical Study Based on Data from Urban Commercial Banks in China. Journal of Financial Research. 2018; (11): 17-29.

[5] Yi X R, Chen Y Y, Wei Y S. Research on Several Major Theoretical Issues about the Digital Economy - Based on the General Analysis of Modern Economics. Economist. 2019; (7): 23-31.

[6] Dai G Q, Fang P F. The Liberalization of Interest Rate and the Risks of Bank - A Study from the Perspective of Shadow Banking and Internet Finance. Finance Forum. 2014; 19(8): 13-19+74.

[7] Qiu H, Huang Y P, Ji Y. How does FinTech Development Affect Traditional Banking in China? The Perspective of Online Wealth Management Products. Journal of Financial Research. 2018; (11): 17-29.

[8] Wang S H, Xie X L. Economic Pressure or Social Pressure: The Development of Digital Finance and the Digital Innovation of Commercial Banks. Economist. 2021; (1): 100-108.

[9] Zang Q Q. Cause and Prevention of Systemic Financial Risk: From the Perspective of Financial and Fiscal Linkage. Finance. 2014; (10): 74-83

[10] Zheng C J, Bhowmik P K. Industry - specific and Macroeconomic Determinants of Non-performing Loans: A Comparative Analysis of ARDL and VECM. Sustainability. 2019; 12 (1): 1-17.

[11] Liu C, Guo F. Officials' Tenure, Central Financial Regulation and Local Banks' Credit Risk. Finance & Trade Economics. 2017; (4): 86-100.

[12] Sun G L, Jiang W. A Study of Mechanism of the Impact of Digital Economics on the Non-performing Loan Rate of Commercial Banks. Securities Market Herald. 2021; (5): 37-44+54.

[13] Sun M L, Wang S E. Research on Credit Risk Identification and Management of Commercial Banks in China. Shandong Social Sciences. 2013; (5): 168-171.

[14] Sun G L, Wang X B, Wang Y. Mechanism of Governmental Over-Intervention Affecting the Non-performing Loan Ratio of Commercial Banks. Shanghai Journal of Economics. 2017; (1): 15-23.

[15] Li Z, Yang S Y. Fiscal Decentralization, Government Innovation Preferences and Regional Innovation Efficiency. Management World. 2018; (12): 29-42.