7. The Essential Role of Big Data: Could it Effectively Mitigate Non-Performing Loans?

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Abstract

Investigating the role of digital technology in non-performing loans is crucial for China to prevent financial risks effectively. This analysis utilises the full-sample and advanced sub-sample methods, utilising quarterly data from the first quarter of 2010 to the fourth quarter of 2022, to examine the interplay between big data and non-performing loans, exploring whether big data serves as an innovative tool to reduce financial risks in China. The conclusions ascertain positive and adverse impacts exist from the big data index (BDI) to the non-performing loan ratio (NPLR). The negative effects point out that the accelerated development of big data technology promotes the reduction of financial risks and vice versa. However, the positive influence would refute this idea; the leading cause is that the economic situation might influence non-performing loans. Conversely, there is a negative effect of NPLR on BDI, highlighting that low NPLR accompanied by economic recovery might facilitate investors to invest in big data-related stocks. Under the background of the fourth industrial revolution and unstable international financial environment, this discussion would provide significant suggestions for China to mitigate non-performing loans by applying big data technology.

Keywords: big data; non-performing loans; time-varying; causal relation; China.

JEL Classification: O33, G38, C32

1. Introduction

This analysis aims to recognise the interrelation between big data and non-performing loans. We also probe whether big data is a new technology to reduce financial risks in China. The government addresses non-performing loans through various institutions, such as the Central Bank and the Securities and Exchange Commission, among others (Anarfo et al., 2020; Liu and Wu, 2023). This approach is integrated into the financial system to avert market failures that could trigger partial or full-scale financial crises (Schuknecht and Siegerink, 2020). The subprime mortgage crisis in the U.S. serves as a stark reminder, exposing regulatory shortcomings like government-induced deregulation and inadequate safeguards for consumers and investors (Groll

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et al., 2021). Addressing gaps in NPL management is paramount to forestall a recurrence of such a crisis (Currie et al., 2022). In the digital economy era (Qin et al., 2023a, c), big data emerges as a pivotal technology for enhancing the management of non-performing loans (Kempeneer, 2021). Big data entails massive volumes of information that necessitate software tools to transform this data into valuable insights, facilitating informed business decisions within reasonable timeframes (Peng et al., 2022; Xu and Zhang, 2022). Its positive influence on non-performing loan management manifests in three key ways: Firstly, big data technology overcomes historical limitations of data scarcity and processing inefficiencies, enhancing the precision of non-performing loan management (Zhao et al., 2022). Secondly, it dismantles information asymmetry barriers that hinder traditional non-performing loan mitigation efforts, broadening the scope and depth of interventions (Su et al., 2023d). Thirdly, big data enables swift data analysis and regulation, accelerating the efficiency of non-performing loan resolution (Du et al., 2021; Jing and Yang, 2022). However, challenges persist. A lack of tight integration between financial institutions and big data technology can undermine non-performing loan management. When big data is applied to credit risk assessment without robust risk warning, exit, and incentive mechanisms, it inadvertently elevates the likelihood of risk events (Cheng et al., 2021). Thus, the intricate relationship between big data and non-performing loan management, though vital, remains under-explored. This discourse underscores the importance of big data in strengthening and refining modern non-performing loan supervision and regulation strategies.

China is chosen as a sample to study the role of big data in non-performing loans, primarily rooted in two pivotal considerations: On the one hand, China stands as the global leader in big data technology, accounting for 39.11% of global big data patent applications as of September 17, 2021, which offers a robust technological foundation for non-performing loans management leveraging big data analytics. In addition, the 14th Five-Year Plan for the Development of the Big Data Industry underscores using big data for actuarial, statistical, and modelling advancements to modernise the financial regulatory system, thereby fostering a conducive policy environment for non-performing loan management grounded in big data insights. On the other hand, China's vast and intricate commercial banking system (Klingelhöfer and Sun, 2018), encompassing a diverse range of financial institutions from large state-owned banks to joint-stock, urban, and rural commercial banks, offers a unique lens into the global banking landscape (Nguyen and Nguyen, 2022). These institutions, with their impressive scale, sophisticated risk management practices, and cutting-edge technology adoption (Liu and Wu, 2023), serve as exemplary models that mirror the broader trends and developments in applying big data within the banking sector (Kempeneer, 2021). As such, China has been strategically chosen as a sample for studying the impact of big data on non-performing loans, providing invaluable insights into how this technology is enhancing risk management capabilities and driving positive outcomes within the banking industry. Thus, it becomes evident that the evolution of big data technology holds a pivotal relationship with non-performing loans in China, a nexus that has yet to be comprehensively explored in existing discourse. Moreover, the intricate and dynamic interplay between them remains underexplored, presenting an opportunity for this work to bridge these gaps.

This study has three contributions: Firstly, previous analyses primarily pay attention to the theoretical analysis of big data and the financial market (Cheng et al., 2021; Du et al., 2021; Kempeneer, 2021), the relationship between innovation and financial risk management (An et al., 2021; Chao et al., 2022; Egorov, 2022; Jing, 2023), as well as the effect of financial technology on financial stability (Daud et al., 2022; Nguyen and Dang, 2022; Wang et al., 2023; Zhao et al., 2023). However, no work offers empirical evidence for the interrelationship between big data and non-performing loans. Thus, this discussion is a groundbreaking work to analyse whether big data is a new technology to mitigate non-performing loans in China. Secondly, most of the previous research on big data is based on theoretical discussion (Cheng et al., 2021; Du et al., 2021; Kempeneer, 2021; Peng et al., 2022; Zhao et al., 2022), which could not provide objective evidence. To cope with this difficulty, we choose the Wind Big Data Concept Index (BDI) to reflect the development of big data. Additionally, this analysis measures the level of non-performing loans by the non-performing loan ratio (NPLR); it is also an innovation in existing research. After that, we select the quarterly sequences from the first quarter of 2010 to the fourth quarter of 2022 to explore the relationship between BDI and NPLR and find that both favourable and adverse impacts of BDI on NPLR exist. The negative influences suggest that big data is a new technology to mitigate non-performing loans, which the positive impact could not support. Conversely, a negative effect of NPLR on BDI exists, underlining that an economic recovery with low NPLR could accelerate the development of big data. These conclusions offer meaningful implications for China to mitigate non-performing loans by establishing a financial data-sharing platform, providing the necessary safeguards, and enhancing the advancement and utilisation of financial big data. Thirdly, the relationship between BDI and NPLR might not be unchanging, which previous research ignores. Thus, the conversation employs techniques for assessing parameter stability as evidence to demonstrate the unsuitability of the full-sample approach. We perform the sub-sample one to identify the changeable relationship between the selected variables. After that, we could offer evidence of whether big data is a new technology to mitigate non-performing loans in China and the role of non-performing loans in big data technology.

The organisation of this discussion follows a logical progression: In Section 2, we undertake a thorough examination and analysis of the extant scholarly works and publications. Sections 3 and 4 delve into the empirical models and data sources. Section 5 thoroughly discusses the quantitative results obtained from the analysis, highlighting significant findings. Finally, Section 6 concludes the discussion by summarising the main conclusions drawn from the study and offering relevant suggestions for practical applications.

2. Literature Review

2.1. *The Theoretical Analysis of Big Data and the Financial Market*

The exploration of the financial market and big data through theoretical analysis has garnered significant interest, with researchers primarily focusing on two distinct angles of investigation. From the standpoint of financial risks, Cheng *et al.* (2021) state that emerging big data approaches can be used to manage financial crime compliance risks, including identity theft, money laundering, market manipulation and financial statement fraud. Du *et al.* (2021) ascertain that big data technology would realise the application of massive credit risk data, which is conducive to making risk forecasting and early warning more accurate and scientific. Kempeneer (2021) suggests that regulators increasingly use big data to understand the health status of banks, and their mindset towards big data requires a novel practical and legal guideline on the effectiveness of data-driven knowledge claims. Wen *et al.* (2021) ascertain that the financial industry could integrate and improve credit risk-related data using advanced big data technology.

From the perspective of financial development, Boubaker *et al.* (2021) reveal that big data has a substantial effect on business and financial decisions because of its cost, scalability and transparency benefits, and it is also a relatively novel and helpful technology to assess the movement of the financial market. Wang (2021) indicates that the development of big data technology could radically change the basis of conditional financial forecasting, and this big data-driven financial prediction plays a significant role in sustainable development. Yu *et al.* (2021) state that applying big data analytics and data-driven culture is essential in implementing supply chain finance. He and He (2022) suggest that the integration of agricultural big data with financial technology holds the potential to address rural financing challenges, particularly those stemming from information asymmetry and farmers' inadequate collateral.

2.2. The Relation between Innovation and Financial Risk Management

The prevailing body of research centres on examining the intricate interplay between innovation and financial risk management. Some scholars explore the effect of innovation on financial risk management. Kero (2013) discovered that financial innovation would increase banks' risk investment preference in both primary and secondary markets, and this impact could be more substantial in an environment with lower macroeconomic risks. After that, the banking system will become less stable as each bank's portfolio is riskier. However, Egorov (2022) proves that innovations that cut costs would assist banks in increasing their equity capital faster and thus decrease risks, while innovations that promote demand could result in a rise in income and a fall in the share of equity capital. Some scholars identify the role of digital technology in financial risk management. Chao *et al.* (2022) underline that regulatory technology proposes to apply artificial intelligence technology to achieve early risk warning, which is also a valuable way to assist in the informatisation and high efficiency of financial risk management. Other scholars identify the mutual influences between them. An *et al.* (2021) highlight that in the U.S., financial risk management and innovation exhibit a mutually reinforcing dynamic adjustment process, whereby each drives the development of the other. Furthermore, they underscore the importance of timely synchronisation between regulatory and innovative strategies during this evolutionary trajectory. Jing (2023) evidence that financial technology has a specific correlation with digital financial risk management; thus, we should focus on applying the former in the latter while developing digital finance.

2.3. The Effect of Financial Technology on Financial Stability

While the effect of financial technology on financial stability has garnered widespread interest, there remains a lack of consensus among experts regarding its overall effects. Some scholars have presented evidence supporting the notion that financial technology positively influences financial stability. Daud *et al.* (2022) indicate that financial technology enhances financial stability by leveraging artificial intelligence, cloud computing, and data technologies, complementing bank concentration. Zhang *et al.* (2023a) present the pivotal role of financial technology in banks' digital risk management framework, specifically in mitigating credit risk. Moreover, it underscores that this mitigating effect becomes even more pronounced as financial technology advances within small and medium-sized banks. Nonetheless, alternative perspectives exist, with some scholars disputing the abovementioned viewpoint. Fung *et al.* (2020) have uncovered that financial technology, when considered without regard to market characteristics, does not significantly impact the vulnerability of financial institutions. Their findings further suggest that the development of financial technology tends to increase (decrease) the fragility of financial institutions in developed (emerging) markets. Phan *et al.* (2020) indicate that the growth of financial technology adversely impacts bank performance in the Indonesian market. Nguyen and Dang (2022) suggest that financial technology development exerts an adverse effect on financial stability in Vietnam, and this impact would be more substantial if the level of financial stability is low.

In China, He *et al.* (2023) reveal that advancements in financial technology can mitigate the risks of corporate debt defaults by alleviating financing constraints, with this effect being more pronounced among high-tech enterprises facing limited investment opportunities. Wang *et al.* (2023) state that the advancement of financial technology can act as a deterrent against management's intentional suppression of adverse information, thereby alleviating information asymmetry and ultimately diminishing the likelihood of stock price crashes. Zhang *et al.* (2023b) underline that regional financial technology positively correlates with the shadow banking activities of non-financial firms, suggesting that it may foster these activities by easing financing constraints. Zhao *et al.* (2023) present that the influence of financial technology on bank risk-taking exhibits functional disparities, with technologies about payment and settlement, capital raising, and investment management demonstrating positive associations. In contrast, market facilitation technology exhibits a negative correlation.

3. Quantitative Models

3.1. Bootstrap Full-Sample Test

Even if the connections among series could be recognised through building the VAR system, these sequences and the system must follow standard normal distributions. According to Su *et al.* (2023a), when this distribution cannot be obeyed, the correctness of the VAR model would be reduced accordingly. In order to address the challenge of non-standard normal distribution in causality tests, Shukur and Mantalos (1997) devised critical values using the residual-based bootstrap (RB) technique, which is then applied to such tests to ensure their validity. The Bootstrap method, a statistical technique, involves resampling from the original data to estimate the distribution of statistics. Based on Qin *et al.* (2023a), the RB method could be appropriate for utilising the VAR process with a small sample. Moreover, Shukur and Mantalos (2000) further contributed by developing the likelihood ratio (LR) test, which offers flexibility for adjustment based on the specific power and size characteristics requirements. The LR test is a hypothesis testing method that compares the goodness of fit of two models. In the context of VAR models, the modified LR test may involve comparing models with and without a specific lag term. The discussion utilises the RB-based revised-LR method to recognise the Granger causality between chosen variables. The following formula denotes the VAR (i) process.

$$Z_t = \chi_0 + \chi_1 Z_{t-1} + \ldots\ldots + \chi_i Z_{t-i} + \upsilon_t \tag{1}$$

where i is chosen by using the SIC, and this method can be utilised to acquire the optimising lag order. Besides, Z is represented as $Z_t = (\mathrm{BDI}_t, \mathrm{NPLR}_t)'$, and Equation (1) is restated as follows:

$$\begin{bmatrix} \mathrm{BDI}_t \\ \mathrm{NPLR}_t \end{bmatrix} = \begin{bmatrix} \chi_{10} \\ \chi_{20} \end{bmatrix} + \begin{bmatrix} \chi_{11}(L) & \chi_{12}(L) \\ \chi_{21}(L) & \chi_{22}(L) \end{bmatrix} \begin{bmatrix} \mathrm{BDI}_t \\ \mathrm{NPLR}_t \end{bmatrix} + \begin{bmatrix} \upsilon_{1t} \\ \upsilon_{2t} \end{bmatrix} \tag{2}$$

Following this formula, we would build the VAR system with the original assumption that BDI does not Granger cause NPLR. If BDI exerts no significant impact on NPLR ($\chi_{21,k} = 0, k \in [1, i]$), the hypothesis would be agreed; when there is a significant influence from BDI to NPLR, we would refuse this supposition. Similarly, the parameters can be utilised to test the initial hypothesis that NPLR does not serve as a Granger cause for BDI. When NPLR exerts no noticeable influence on BDI, the original supposition can be agreed upon, and vice versa.

3.2. Stability Tests of Parameters

The above methodology offers flexibility and precision in causal analysis and handles non-standard distributions via RB and modified LR tests. However, it is assumed by the full-sample method that the parameters are unchanging (Qin et al., 2023b), whereas this hypothesis cannot always hold in reality (Li et al., 2023). The conventional method can be unreliable because the VAR process coefficients may undergo structural mutations. Hence, to enhance accuracy, this analysis employs the Sup-F, Ave-F, and Exp-F tests by Andrews (1993) and Andrews and Ploberger (1994). The Sup-F test identifies structural shifts in individual series and VAR models, while the Ave-F and Exp-F tests assess gradual changes over time. In addition, the Lc statistics, introduced by Nyblom (1989) and Hansen (1992), are used to verify if the parameters exhibit random walk behaviour. In cases of structural mutations in series or the VAR system, the relationship between BDI and NPLR becomes variable (Su et al., 2023b). Therefore, recognising the limitations of full-sample analysis, we adopt a sub-sample approach to capture the time-dependent relationship between the selected variables.

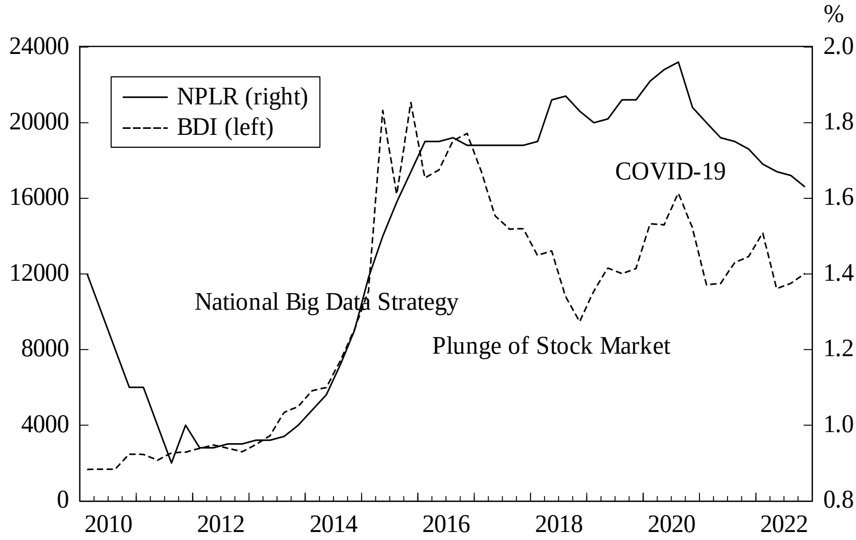
3.3. Bootstrap Sub-Sample Test

The sub-sample approach, initially devised by Balcilar *et al.* (2010; 2013), explores the dynamic relationship between two series over time. This methodology involves dividing the entire dataset into a series of smaller, overlapping segments, or subsets, using a sliding or rolling window of a fixed width. As this window moves consecutively along the data series, it allows for the analysis of the relationship between the two series to be examined at different points in time, revealing its time-varying characteristics. However, selecting an appropriate width poses a challenge; a wider window reduces frequency, while a narrower one risks inaccuracy. Pesaran and Timmermann (2005) address this issue, recommending a minimum width of 20 when the VAR(i) coefficients are not constant. The specific steps are as follows: First, set the total sequence length as G and the window width as h, defining subsets from h to G. Second, apply the RB-adjusted LR test to each subset to analyse the relationship within each subset. Third, p-values and LR statistics are chronologically calculated to obtain the estimated outcomes. Furthermore, averages of these estimates ($N_b^{-1}\sum_{k=1}^{i}\hat{\chi}^{*}_{21,k}$ and $N_b^{-1}\sum_{k=1}^{i}\hat{\chi}^{*}_{12,k}$) indicate the influence of BDI on NPLR and vice versa. To ensure robustness, a 90% confidence interval, with upper and lower bounds defined by the 95th and 5th quantiles, is employed in the analysis (Qin et al., 2023b, c).

4. Data

This analysis chooses the quarterly sequences from the first quarter of 2010 to the fourth quarter of 2022 to explore if big data is a new technology to mitigate non-performing loans in China. In 2010, the non-performing loan management in China strengthened significantly, primarily because: On the one hand, the intense turbulence caused by the global economic crisis required China to take the initiative to enhance forward-looking regulation, such as reasonably controlling the total amount of credit. On the other hand, the European sovereign debt crisis has exposed many shortcomings of the supervision system inside the European Union and the euro area, which has brought beneficial enlightenment to improve China’s financial regulation, such as introducing the idea of counter-cyclical supervision and transitioning to mixed systemic management. Since then, China has continuously strengthened and improved modern financial supervision and regulation to resolve long-standing and prominent problems in the financial sector. This exploration measures the level of non-performing loans by the non-performing loan ratio (NPLR), which refers to the proportion of non-performing loans in the total loan balance of commercial banks (Kryzanowski et al., 2023; Liu et al., 2023). Meanwhile, the advent of digital technologies such as big data has ushered in the third wave of information technology (e.g., big data) since 2010 (Chen et al., 2022; Viana et al., 2022), which may enrich the ways and means of financial regulation in China. Then, we employ the Big Data Concept Index (BDI) as a metric to gauge the progression of big data technology (this index code is 884131.WI), a practice commonly adopted by academia (Qin et al., 2023a, c) to mirror the broader technological advancements in data storage, computing, and mining. In addition, the higher BDI points out that the relevant stocks attract more investments, encouraging the development of big data and vice versa. While acknowledging that this index does not explicitly target the banking sector, it offers a macro-level perspective that captures the technology’s evolution within the economy. Furthermore, we argue that the widespread adoption of big data technology across industries, including finance, indirectly reflects its potential impact on non-performing loan management. After that, we can identify the interrelationship between BDI and NPLR and further probe whether big data is a new technology to mitigate non-performing loans in China. Figure 1 draws the trends of BDI and NPLR.

Figure 1. The trends of BDI and NPLR



It is perceived from Figure 1 that NPLR is not always different in direction from BDI. Since China tightened its non-performing loan management in 2010, NPLR has decreased from 1.4% in the first quarter of 2010 to 0.9% in the third quarter of 2011, and then it remained at no more than 1% until the fourth quarter of 2013. During the same period, BDI increased from 1652.403 in the first quarter of 2010 to 4977.063 in the fourth quarter of 2013, which grew by more than 200%. However, both BDI and NPLR show a significant upward trend, where the former increases from 5813.258 in the first quarter of 2014 to 21055.287 in the fourth quarter of 2015 (which grows by more than 250%), and the latter raises from 1.04% to 1.67% at the same time. The plunge in the Chinese stock market made BDI sharply fall to 9471.569 in the fourth quarter of 2018, which decreased by about 55%, but NPLR still shows an upward trend that increased to 1.83%. Affected by COVID-19, the economic recession has pushed NPLR up to 1.96% in the third quarter of 2020, and BDI also rose by more than 70% to 16267.642, which presents a similar momentum in these two series. As the economy begins to recover, NPLR falls to 1.63% in the fourth quarter of 2022, while BDI tends to fluctuate. Based on the above discussion, the relationship between BDI and NPLR is not unchanging but intricate. The VAR and SVAR models cannot be used to catch the complicated Granger causality between chosen sequences. Accordingly, employing sub-sample one is reliable for recognising these changeable and complex mutual influences between BDI and NPLR. Whether big data is a new technology to mitigate non-performing loans could also be resolved.

Table 1. Descriptive statistics for BDI and NPLR

	BDI	*NPLR*
Observations	52	52
Mean	10135.68	1.486
Median	11446.01	1.670
Maximum	21055.29	1.960

Minimum	1652.403	0.900
Standard Deviation	5848.259	0.363
Skewness	-0.059	-0.437
Kurtosis	1.811	1.519
Jarque-Bera	3.096	6.405**
Probability	0.213	0.041

*Note: Significance is indicated at a 5% level with **.*

Table 1 indicates that the mean values of BDI and NPLR are 10135.68 and 1.486, respectively, suggesting a concentration around these levels. Notably, the BDI series exhibits significant volatility, with its maximum value nearly 13 times greater than its minimum. Both BDI and NPLR show negative skewness, indicating a left-skewed distribution. Their kurtosis values mean platykurtic distributions, characterised by relatively flat peaks and thin tails. The Jarque-Bera test suggests that the null hypothesis, which assumes a normal distribution for NPLR, is rejected with a statistical significance of 5% while accepting it for BDI, indicating a departure from normality for NPLR. Consequently, the standard Granger causality test within the VAR framework may not be appropriate. To address this, we utilise the RB-adjusted revised-LR approach. Additionally, we transform BDI by taking its logarithm and first difference to mitigate the effects of extreme fluctuations and spurious regression.

5. Empirical Results and Discussions

The analysis chooses the ADF (1981), PP (1988) and KPSS (1992) techniques to prove the stationarity in BDI and NPLR. Furthermore, to gain a deeper insight into the unit root properties amidst potential structural transformations, we apply the Zivot-Andrews (ZA) test, pioneered by Zivot and Andrews in 1992. Table 2 summarises the outcomes of this refined unit root test, revealing that both the BDI and NPLR series display stationarity. Critically, the ZA test validates the existence of structural breaks within these series across the entire sample period, highlighting the dynamic nature of their underlying trends.

Table 2. The outcomes of unit root tests

	ADF	*PP*	*KPSS*	*ZA*
BDI	-4.225 (1)***	-8.687 [2]***	0.181 [1]	-8.829 (1)***
NPLR	-3.059 (1)**	-4.112 [4]***	0.182 [5]	-3.417 (2)**

*Notes: The parenthetical values show the optimal lag order (SIC) and the selected bandwidth (Newey-West). The symbols *** and ** signify statistical significance at the 1% and 5% levels.*

Using Equation (2), a VAR(i) system is constructed for full-sample analysis, with an optimal lag order of 3 determined by SIC. Table 3 reveals no Granger causality between BDI and NPLR in either direction. However, the conclusion is inconsonant with the extant efforts (An et al., 2021; Cheng et al., 2021; Du et al., 2021; Kempeneer, 2021; Chao et al., 2022; Daud et al., 2022; Egorov, 2022; Jing, 2023; Wang et al., 2023; Zhao et al., 2023).

Table 3. The outcomes of the bootstrap full-sample technique

H0: BDI is not the Granger cause of NPLR		*H0: NPLR is not the Granger cause of BDI*	
Statistic	p-value	Statistic	p-value
4.726	0.140	0.927	0.770

Notes: This investigation calculates p-values through the execution of 10,000 bootstrap replications.

This approach assumes constant coefficients in the VAR(i) system, recognising causality consistently across the entire sample (Su et al., 2023a, b). Subsequently, the analysis employs Sup-F, Ave-F, Exp-F, and Lc statistics, with their results presented in Table 4.

Table 4. The outcomes of parameter stability techniques

Tests	*BDI*		*NPLR*		*VAR (i) system*	
	Statistics	p-values	Statistics	p-values	Statistics	p-values
Sup-F	146.493***	0.000	143.866***	0.000	52.948***	0.000
Ave-F	31.211***	0.000	22.371***	0.000	14.878***	0.002
Exp-F	69.609***	0.000	68.295***	0.000	22.871***	0.000
Lc					1.827**	0.030

*Notes: *** and ** reveal the significance at 1% and 5% levels.*

The Sup-F methodology rejects the null hypothesis with a high degree of statistical significance (at the 1% level), thereby suggesting the occurrence of sudden structural alterations within the BDI, NPLR, and the VAR(i) system. Similarly, the Ave-F and Exp-F methods also reject the null hypothesis at the 1% level, confirming that the variables and coefficients in the VAR(i) model significantly vary over time. Moreover, the Lc statistics uphold the alternative hypothesis at a significance level of 5%, confirming that the VAR(i) model deviates from a random walk pattern. BDI has a dynamic and changeable relationship with NPLR; hence, the discussion utilises sub-sample one (Qin et al., 2023a, b) to catch this intricate conduction mechanism between BDI and NPLR. According to Pesaran and Timmermann (2005), the analysis sets the width as 20 quarters.

Figures 2 and 3 illustrate the p-values and coefficients of BDI's impact on NPLR. Significant Granger causality from BDI to NPLR is observed at the 10% level during specific periods: from the fourth quarter of 2015 to the first quarter of 2016, the third quarter of 2019 to the third quarter of 2020, and the second quarter of 2022 to the fourth quarter of 2022. Notably, these periods encompass negative (the fourth quarter of 2015 to the first quarter of 2016 and the second quarter of 2022 to the fourth quarter of 2022) and positive (the third quarter of 2019 to the third quarter of 2020) effects of BDI on NPLR.

Figure 2. Testing the null hypothesis that BDI does not Granger cause NPLR

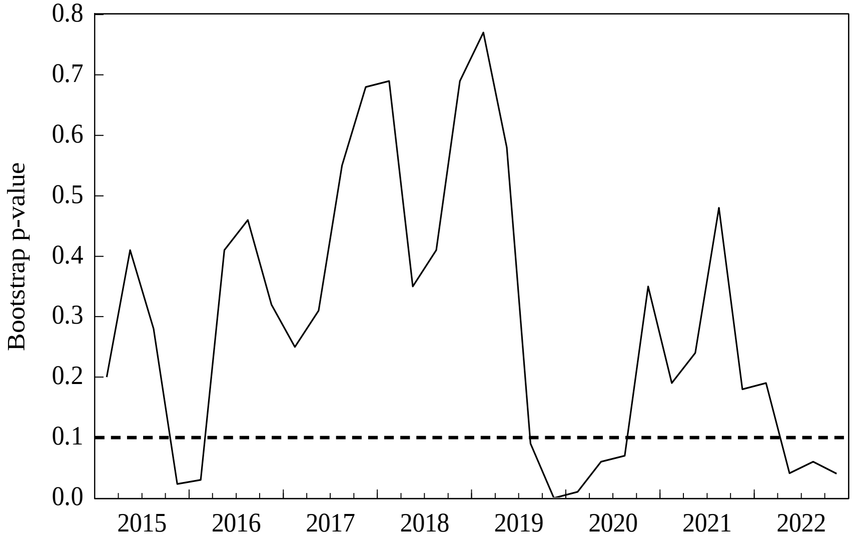
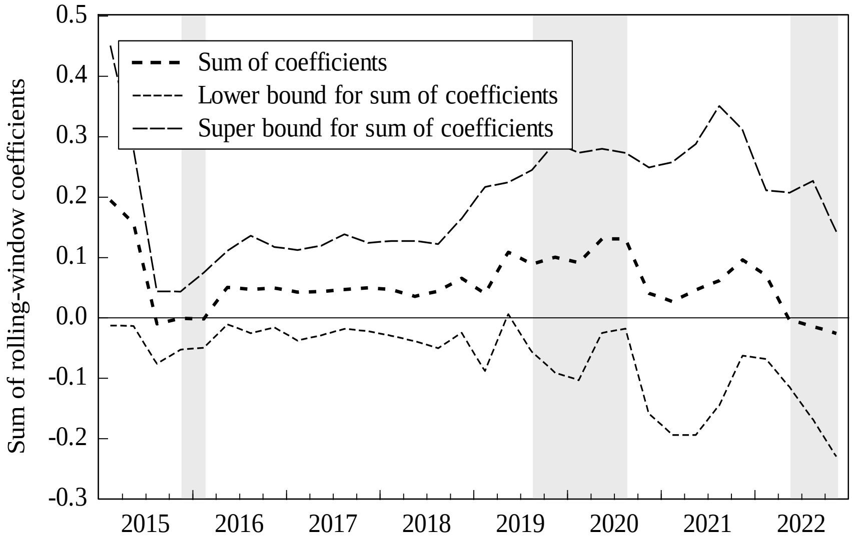


Figure 3. The coefficients of the influence from BDI to NPLR



From the second quarter of 2022 to the fourth quarter of 2022, BDI rebounds from 11209.856 to 12023.169 (which grows by 7.26%); the primary cause of this slight increase can be interpreted as: The promulgation and implementation of relevant policies have created a favourable environment for the development of big data， such as China intends to establish a comprehensive data-centric system. These national policies have shed light on the future direction of big data (Teixeira and Tavares-Lehmann, 2022), encouraging investors to enhance their focus and pour funds into big data-related assets, which drives BDI to rise. However, NPLR reduced from 1.67% to 1.63 during the same period, and this negative influence from BDI to NPLR can be illustrated in several ways. Firstly, high BDI suggests that big data development has accelerated, and applying big data technology is conducive to forming a financial risk prevention system. To be specific, the practical analysis of massive data using big data technology can help financial institutions grasp the credit status of individuals and the business status of enterprises timely and comprehensive. Then, the adverse selection behaviour caused by information asymmetry (Kosenko et al., 2023) would be reduced, which improves credit quality and establishes a reliable credit relationship. Hence, the non-performing loan management could be enhanced accordingly, resulting in a decline in NPLR. Secondly, the development of big data accompanied by high BDI could enhance the accuracy of financial data analysis results and then improve the reliability of decision-making, expand the scope of non-performing loan management, making the related authorities comprehensively understand the actual financial activities of the supervision subject; analyse financial data in a short period, to improve the efficiency of non-performing loan management (Kempeneer, 2021). As non-performing loan management gradually improved, NPLR naturally showed a downward trend. Thirdly, high BDI increases the returns of securities investors (Dai et al., 2022); they have more income to repay the loans, which leads to an evident decrease in non-performing loans, further causing NPLR to fall. Consequently, we can prove that the accelerated progress of big data promotes improving non-performing loan management. BDI negatively impacts NPLR from the second quarter of 2022 to the fourth quarter of 2022.

However, the above view that big data is a new technology to improve non-performing loan management could not be supported by the positive effect of BDI on NPLR. From the third quarter of 2019 to the third quarter of 2020, BDI shows an upward momentum, increasing from 12000.959 to 16267.642, which rises by about 35%. This apparent increase can be attributed to two causes: On the one hand, with the opening of the 5G commercial era in 2019, the topic of science and technology continues to rise (Lee and Yu, 2022). Both institutional investors, northbound capital, floating capital and retail investors show enthusiasm for relevant stocks, which increases BDI. On the other hand, COVID-19 in 2020 made online education, online health care and other concepts popular, causing technology stocks (including BDI) to rise sharply (Qin et al., 2023a, c; 2024c). Although the development of big data should have enhanced financial regulation, NPLR shows an upward trend, which increases from 1.86% in the third quarter of 2019 to 1.96% in the third quarter of 2020. The leading cause behind this phenomenon is the economic situation. In 2019, the trade conflicts between China and the U.S. weakened China’s foreign trade (the total value of exports and imports decreased from 4622.44 billion dollars in 2018 to 4577.89 billion dollars in 2019) and investment (the outward direct investment flows decreased from 143.04 billion dollars in 2018 to 136.91 billion dollars in 2019), which has an adverse impact on the economic development (Su et al., 2022; 2023c). In 2020, COVID-19 severely disrupted many industries, with some companies shutting down factories and forcing employees to lose their jobs (Zhong and Lin, 2022), seriously damaging the economy (real economic growth in the first quarter of 2020 was -6.8%[5]). In the economic downturn, the ability of borrowers to repay their debts is significantly weakened, which might cause considerable non-performing loans (Benavides-Franco et al., 2023; Kryzanowski et al., 2023) and then push NPLR up even if BDI is at a high level. Hence, the positive influence of BDI on NPLR from the third quarter of 2019 to the third quarter of 2020 could be ascertained.

[5] *The data is obtained from the National Bureau of Statistics of China.*

Figures 4 and 5 display the p-values and coefficients indicating that NPLR Granger causes BDI at the 10% significance level from the first quarter of 2021 to the fourth quarter of 2021. During this period, a negative effect is observed from NPLR to BDI.

Figure 4. Testing the null hypothesis that NPLR does not Granger cause BDI

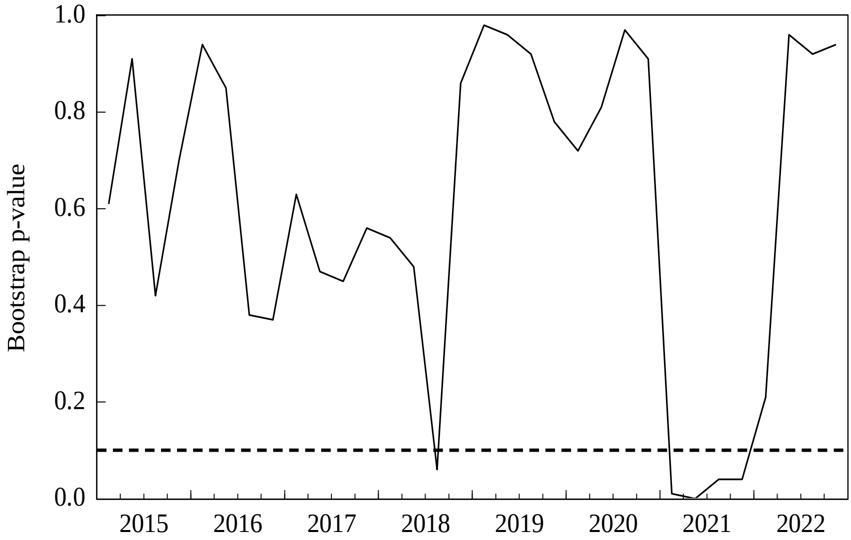
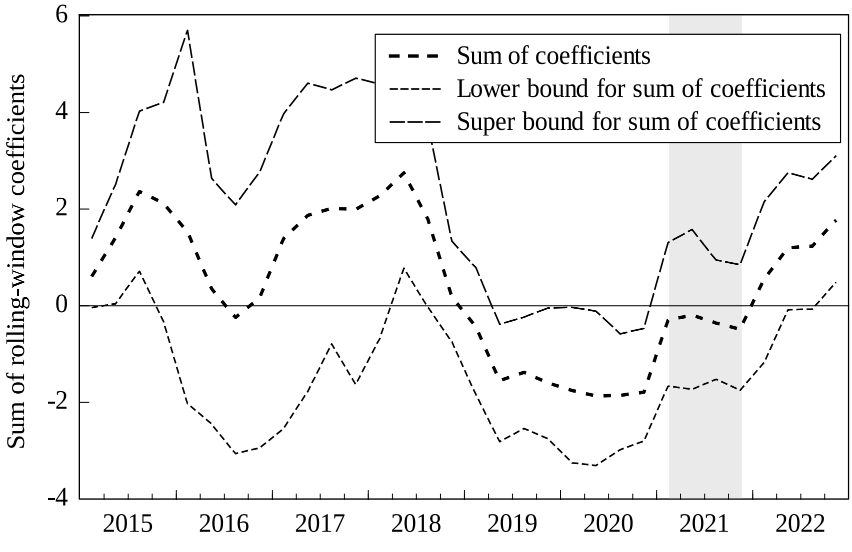
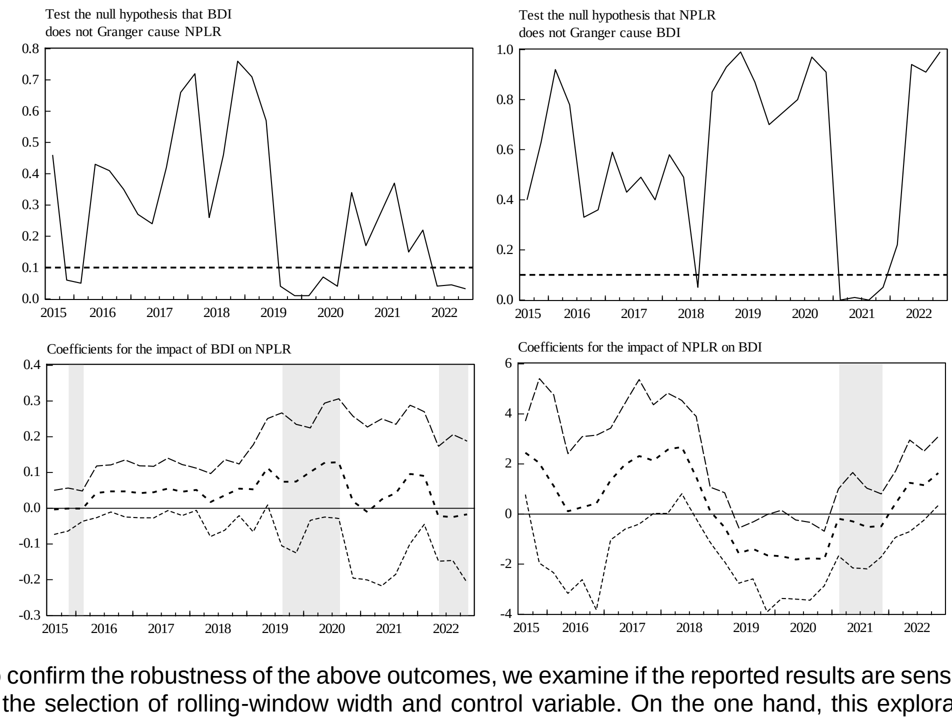


Figure 5. The coefficients of the influence from NPLR to BDI



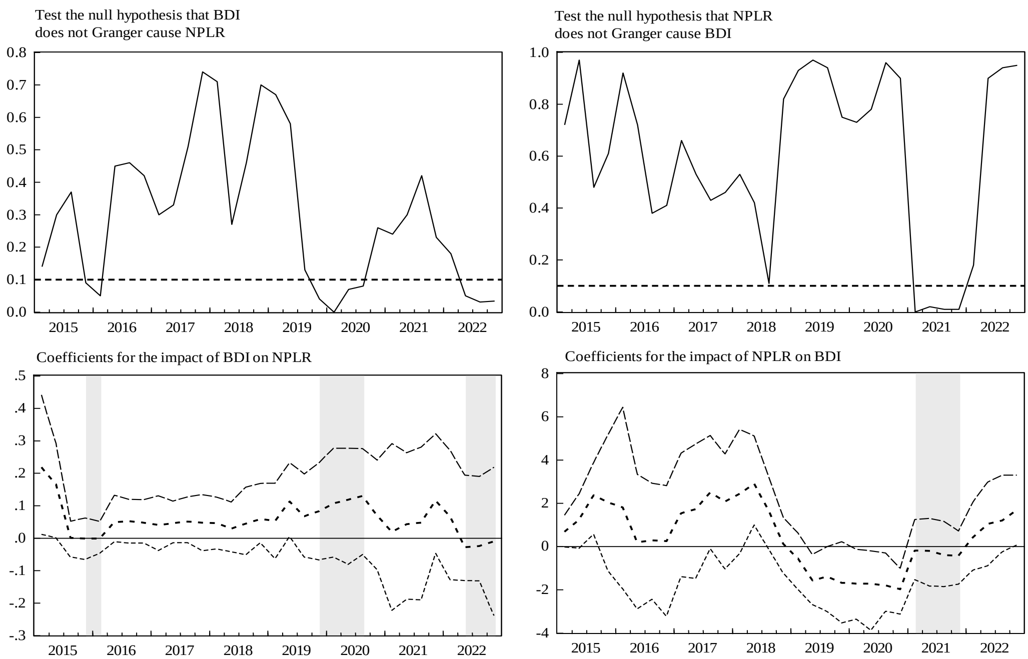
From the first quarter of 2021 to the fourth quarter of 2021, NPLR decreases from 1.8% to 1.73%, mainly due to the economic recovery in China. As the adverse impacts of COVID-19 on China's economy dissipate, real gross domestic product (GDP) growth has reached 8.4% this year. Against this background, the income of individuals has increased significantly (per capita disposable income grows by 8.1%), and the unemployment rate has decreased obviously (the registered urban unemployment rate reduced from 4.2% in 2020 to 4% in 2021). Besides, businesses have also resumed normal production operations, allowing them to recoup the losses caused by COVID-19 and make a profit (Zhong and Lin, 2022; Qin et al., 2023a, c). After that, more borrowers have enough income to repay the loans, which leads to a decline in NPLR (Benavides-Franco et al., 2023; Kryzanowski et al., 2023). During the same period, BDI increased from 11409.299 to 12915.392, growing by nearly 15%; this negative effect of NPLR on BDI can be stated as follows: An economic recovery with low NPLR not only makes the individuals and enterprises have more incomes but also gives investors' confidence about the future economic development in China, making them more willing to invest instead of savings. Then, they are inclined to invest in the Chinese stock market to earn returns, especially the technology stocks (e.g., big data-related stocks), which causes BDI to rise accordingly. Thus, we provide proof of the negative impact of NPLR on BDI during the first quarter of 2021 to the fourth quarter of 2021.

Figure 6. The result of changed rolling-window width (22 quarters)



To confirm the robustness of the above outcomes, we examine if the reported results are sensitive to the selection of rolling-window width and control variable. On the one hand, this exploration employs the width as 22 quarters, and the result of the changed rolling window width is revealed in Figure 6. Although we changed the width, the outcome was similar to that with a window width of 20 quarters. On the other hand, the relationship between economic development and NPLR is intricately intertwined. During economic booms, as businesses flourish and individual incomes rise, credit default risks diminish, decreasing NPLR. Conversely, in times of economic downturns, heightened operational challenges for businesses and increased unemployment rates translate into weakened repayment capabilities, which in turn tend to elevate NPLR. As such, economic development may exert a noticeable effect on the relationship between BDI and NPLR; thus, we choose China's gross domestic product (GDP) growth rate as a control variable, and the results are shown in Figure 7. It could be observed that after incorporating control variables into the analysis, the results remain broadly consistent, reinforcing the persuasiveness of the correlation between BDI and NPLR. Therefore, it can be concluded that the reported outcomes and related discussions are reliable and robust, but they are not sensitive to the width and control variable choice.

Figure 7. The result of added control variable (GDP growth rate)



Four-parameter stability tests reveal that BDI, NPLR, and the VAR(i) model coefficients undergo sudden structural changes. Thus, a full-sample approach is inadequate, and we adopt a more sophisticated sub-sample method to capture the time-dependent relationship between the variables. The sub-sample analysis confirms both positive and adverse effects of BDI on NPLR. The negative effects imply that a high BDI may significantly reduce non-performing loans, suggesting that big data technology can mitigate financial risks. However, this viewpoint lacks support from the positive influence that BDI exerts on NPLR, primarily due to NPLR would increase under the adverse impacts of economic downturn or recession (e.g., the Sino-U.S. trade disputes and COVID-19), which weakens the role of big data in mitigating non-performing loans. In turn, the decrease in NPLR negatively influences BDI, underlining that low NPLR accompanied by economic recovery and development would encourage investors to invest in big data-related stocks. Additionally, we conduct robustness checks by varying the rolling window size and incorporating a control variable. These tests aim to validate the reliability of our reported findings and associated discussions.

6. Conclusions and Suggestions

The discussion studies the transmission mechanism between big data and non-performing loans and further resolves whether big data is a new technology to reduce financial risks in China. By analysing quarterly data spanning from the first quarter of 2010 to the fourth quarter of 2022, we utilise the full-sample approach and the relatively advanced sub-sample method to explore the relationship between BDI and NPLR. The outcomes state that BDI has positive and adverse impacts on NPLR. Among them, the negative impacts state that the accelerated development of big data technology promotes the improvement of non-performing loan management while the slow progress impedes it. However, this view is not drawn from the positive effect of BDI on NPLR; the leading cause is that the economic recession during the Sino-U.S. trade disputes and COVID-19 inevitably cause the non-performing loans to increase even if there is a development in big data technology. Conversely, there is a negative impact of NPLR on BDI, suggesting that an economic recovery with low NPLR brings investors more confidence to invest in technology stocks such as big data-related stocks. Moreover, by changing the width of the rolling window and adding a control variable, we could evidence the robustness of the reported results. By studying the changing relationship between BDI and NPLE, it is concluded that big data is not always a new technology to mitigate non-performing loans, which is also determined by the economic situation.

By comparison, while existing studies have primarily focused on theoretical analyses of big data and financial risks, our work presents empirical evidence for the interrelationship between big data and non-performing loans in China. This empirical approach provides a more robust foundation for understanding the role of big data in financial risk mitigation. Second, our study utilises the Wind Big Data Concept Index (BDI) as a proxy for the development of big data technology, representing an innovation in measurement compared to previous studies. By using quarterly data spanning over a decade, we are able to capture the relationship between BDI and NPLR. Third, in contrast to previous studies that assume a static relationship, our sub-sample analysis demonstrates the dynamic relationship between BDI and NPLR. This finding underlines the importance of considering dynamic changes in financial risk management strategies and policymaking.

The findings have significant economic implications for China, which is grappling with high non-performing loans due to the development of big data technology. Firstly, the negative effect of BDI on NPLR highlights the potential of big data technology as a powerful tool for risk mitigation. Policymakers should explore and establish a financial data-sharing platform to encourage innovation in the regulatory system. Based on this platform, China can comprehensively analyse financial institutions' legal adherence, operational management, and risk mitigation strategies across diverse regions, assessing the prevailing issues and the robustness of their risk management frameworks. Also, the real-time analysis technology of this platform is used to establish and enhance the credit investigation system of enterprises and individuals, realise integrated risk prediction and supervision, and effectively improve the ability to prevent financial risks. Secondly, the reciprocal relationship between NPLR and BDI underscores the importance of a stable and healthy financial system for fostering technological innovation. During economic downturns, policymakers should prioritise measures to reduce non-performing loans and stabilise the banking sector, as this could have positive spillover effects on the development of big data. Finally, the dynamic relationship between BDI and NPLR suggests that risk management strategies and policies must be flexible and adaptive. Policymakers should regularly reassess the effectiveness of existing risk management frameworks and adjust them as necessary to keep pace with changing market conditions and technological advancements. Consequently, the research provides valuable insights into the role of big data in mitigating financial risks associated with non-performing loans in China. By presenting empirical evidence and highlighting the time-dependent nature of the relation between them, our work contributes to the growing body of knowledge on financial risk management in the digital age.

While this article has made notable progress in exploring the role of big data in reducing non-performing loans in China, there are two main limitations. Firstly, the research data primarily focuses on quarterly sequences, failing to encompass real-time data over shorter or longer periods, which may constrain the timeliness and dynamics of the analysis. Secondly, the study emphasises the macroeconomic impact of big data development without delving into how specific financial institutions apply big data technology and its actual effects, resulting in a lack of in-depth micro-level analysis. To address these shortcomings, future research can delve deeper in two directions: Firstly, adopt high-frequency or more granular time-series data to capture the immediate effects of big data technology applications and analyse their real-time impact on financial market dynamics. Secondly, through case studies, surveys, or other methods, delve into how financial institutions utilise big data in operations and evaluate its specific contributions to non-performing loan management, providing a more nuanced empirical basis.

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