DIGITALIZATION AND BANK LENDING

YUAN SUN

MPhil

The Hong Kong Polytechnic University

2023

The Hong Kong Polytechnic University

School of Accounting and Finance

Digitalization and Bank Lending

Yuan Sun

A thesis submitted in partial fulfilment of the requirements for the degree of Master of Philosophy

April 2023

CERTIFICATE OF ORIGINALITY

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

(Signed)

Yuan Sun___________________ (Name of student)

ABSTRACT

In this study, I document that the level of IT information technology (IT) adoption in banks is positively related to loan loss provision (LLP) timeliness. Utilizing the past number of local banks' data breach cases as an instrumental variable (IV) for banks' IT adoption level, I conduct an IV analysis to support that IT adoption in banks can improve timely LLP recognition. This relation is more pronounced for banks with more geographically-dispersed branches and for banks with a high level of digital human capital, which indicates a significant proportion of staff capable of using IT analytical tools to assess bank loan credit risk. I further find that banks' IT adoption level is positively related to several proxies for banks' internal information environment quality (i.e., the speed of banks announcing earnings after the fiscal period ends, a lower likelihood of restatements, or of delaying SEC financial report filing). I also find that the IT adoption level of banks is positively associated with the probability of using credit risk models.

Keywords: Loan loss provisions, IT adoption, timeliness, digital human capital, internal information environment

ACKNOWLEDGEMENT

I would like to express my sincere gratitude to my supervisors, Prof. Walid Saffar and Dr. Nan Yang, for their inspiring guidance, constant encouragement and help throughout the period of my M.Phil. study and in the preparation of this thesis. I would like to thank my collaborators Dr. Feng Tian and Prof. Sean Xin Xu for discussions in the research aspect of this thesis. I would like to thank Prof. Jie Cao, Prof. Wayne W. Yu, and Dr. Byron Y. Song for their precious time to read my thesis and serve on the committee. I would also like to thank Prof. Steven Ongena, Dr. Lai Wei, and Dr. Wensi Xie for collaborations in other research projects.

I feel grateful to my colleagues and friends, for their continued encouragement, support, and help. They are a group of honest people with a genuine passion for academic research and inspiring ideas.

The utmost gratitude is for my family. Their company and support are the main reasons I have survived this strenuous research journey.

TABLE OF CONTENTS

1. INTRODUCTION

Banks play a central economic role in reducing information asymmetry between depositors and borrowers through selecting and monitoring borrowers (Diamond 1984), and information technology (IT) is an integral component of banks' intermediation functions that enhances banks' output and competitiveness (Marquez and Hauswald 2003; Berger, Frame, and Miller 2005; Koetter and Noth 2013). Consistent with this view, investment in IT in the U.S. banking industry has increased six-fold over the past two decades (Modi et al. 2022), a scale that is much larger than that in other industries.[1] Moreover, recent studies find that bank IT investment improves loan quality and increases credit supply (Core and De Marco 2023; Kwan et al. 2023; Pierri and Timmer 2022).

Little is known, however, about the role that IT investment plays in banks' internal information management and financial reporting choices. This role is important because banks' reporting and disclosure practices have significant implications for banks' transparency and risk-taking and ultimately for financial system stability (e.g., Beatty and Liao 2011; Bushman and Williams 2012, 2015).[2] Given the recent policy debate on the financial stability consequences of IT (Boot et al. 2021; Carletti et al. 2020; Claessens et al. 2018; FSB 2019), research on the financial reporting implications of bank IT investment is needed.

In this paper, I conduct the first evaluation of the impact of IT investment on financial reporting choices for banks. To this end, I focus on the timeliness in banks' loan loss provisions (LLPs). LLPs constitute the dominant component of bank accruals, and their timeliness has been a central topic in academic and policy discussions (e.g., Beatty and Liao 2011; Bushman and Williams 2012, 2015; U.S. Government Accountability Office 2013). I hypothesize that a high level of IT adoption enables banks to recognize LLPs in a timely manner for several

[1] See https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/breakthrough-it-banking, last accessed on April 26, 2023.

[2] For the recent surveys of the literature on banks' financial reporting, see Beatty and Liao (2014), Bushman (2014), and Acharya and Ryan (2016).

reasons. IT applications can automate banks' information processing, integrate credit information about borrowers and clients from different industries and locations, and extract new information from alternative unstructured data. The substantial improvements in banks' information sets in turn enhance managers' estimates of LLPs and lead to timelier loan loss provisioning decisions (Balakrishnan and Ertan 2021; Yang 2022). Moreover, IT enhances banks' internal controls (Masli et al. 2010; Chapman and Kihn 2009), thereby improving the monitoring of loan loss recognition processes and reducing potential control risks for loan management. The development of data analytical IT further supports the use of credit analysis models when analyzing bank loans and forecasting loan losses (Deloitte 2019; Wu, Zhang, and Zhou 2022), which can in turn improve LLP timeliness (Bhat, Ryan, and Vyas 2019).[3]

However, intensive IT investment may not necessarily help banks recognize loan losses in a timely manner. Investment in IT may create additional uncertainty in bank operations because IT investment is accompanied by uncertainty about its economic impact, technological complexity, rapid obsolescence, and implementation challenges (Dewan and Ren 2011; Dewan, Shi, and Gurbaxani 2007). Such uncertainty may cause disruption to bank loan analyses for understanding potential loan losses. Furthermore, a long-lasting concern regarding IT applications in banking is that "hard information" is easier to report and communicate than "soft information", potentially causing banks to neglect the latter for loan analysis when IT applications are used intensively (Rajan, Seru, and Vig 2015). Although advancements in communication technology and recent attempts of fintech to gradually harden soft information (Liberti and Petersen 2019) may mitigate such a concern, it remains empirically unclear whether the neglect of soft information can be entirely overcome.

[3] In Section 2, I further detail my hypothesis about the effect of IT adoption on banks' LLP timeliness.

To test my hypotheses, I utilize the Harte Hanks Market Intelligence Computer Intelligence Technology database, which provides firm-level comprehensive IT information.[4] Combining this information with banks' financial information from Compustat leads to a bank panel dataset from 2011 to 2019, including 7,601 bank-quarter observations for 359 public banks. To proxy for a bank's IT adoption level, I use the natural logarithm of its budgeted IT spending per employee. I measure a bank's LLP timeliness by estimating the incremental explanatory power of contemporaneous and future nonperforming loans in determining the current LLP, beyond that of past nonperforming loans (Nichols, Wahlen, and Wieland 2009; Beatty and Liao 2011).

I find that a higher level of IT adoption by banks has a positive effect on LLP timeliness. This effect of bank IT adoption is economically sizeable: A one-standard-deviation increase in IT spending is associated with a 25 percent increase in LLP timeliness relative to the sample mean value. This positive relation remains when the regressions further include bank primary business mode fixed effects (FEs), year-quarter FEs, bank headquarters state FEs, and bank characteristics. This finding is also robust to a variety of alternative specifications, such as employing alternative measures for the level of IT adoption, using alternative sets of FEs, clustering standard errors differently, and using other measures of LLP timeliness.

To further address the concern that the relation between banks' IT adoption level and LLP timeliness might be endogenously determined, I use the past number of local data breach cases in neighboring banks as an instrumental variable (IV) for banks' IT adoption level, based on prior studies (e.g., Li, Leung, and Yue 2023). The IV regression results support the finding that a high level of IT adoption in banks has a positive effect on LLP timeliness.

[4] This dataset is widely used in the economics and finance literature for studying the implications of technology adoption in both the non-financial sector (Bloom et al. 2014; Forman, Goldfarb, and Greenstein 2012) and, very recently, the financial sector (He et al. 2022; Kwan et al. 2023). It is also called Aberdeen's Computer Intelligence Technology data.

If banks' IT adoption is positively related to LLP timeliness through improving the internal information environment of banks, I expect that banks' IT adoption will have a bigger effect on LLP timeliness among banks with branches located farther away from the headquarters. Greater IT infrastructure enables banks to better integrate all the credit information about borrowers and clients across their branches (Berger 2003). Improvements in banks' information sets in turn help banks evaluate risks more effectively, enhancing their loan loss provisioning decisions (Balakrishnan and Ertan 2021). As distance raises the cost of access to information, a high level of IT adoption should have a larger impact on banks whose branches are more distant from their headquarters. Following Levine et al. (2020), I construct three proxies for a bank's geographical dispersion: (1) the sum of the total distance (in kilometers) for each branch to the main office, (2) the deposit-weighted average distance (in kilometers) between a bank's headquarters location and its branches, and (3) the total number of branches. I find that the timeliness effects of IT spending are more pronounced for banks with more geographically dispersed branches.

If banks' advanced IT adoption improves the analysis and understanding of bank loan risks and losses, thereby leading to timely LLP, I expect that the effect of IT adoption in banking on LLP timeliness in banks is greater when banks have a high level of digital human capital. This high level implies that a high proportion of staff is capable of using IT analytical tools. Digital-capable employees are expected to better understand IT, specifically how processes, hardware, software, and networks interconnect to support the firm's financial reporting objectives (Abernathy et al. 2023). I proxy the level of digital human capital in a bank by constructing an indicator for whether the percentage of employees (e.g., the percentage of accounting/finance employees) with digital skills is greater than that of an average bank in our sample. I find that banks' IT adoption has a positive impact on LLP timeliness only in banks with adequate digital human capital. In contrast, for banks with inadequate digital human capital, the IT adoption level has little bearing on their LLP timeliness. These findings are robust to different measures of the fraction of bank employees with digital skills.

In addition, I conduct two sets of analyses regarding how banks' IT adoption level affects timely LLP recognition. First, I test whether banks' internal information environment improves with their IT adoption level. A high IT adoption level should enhance a bank's ability to collect, process, and consume information within and across bank units, improving its internal information quality. Improved internal information quality could facilitate managerial decision-making (e.g., Gallemore and Labro 2015), including decisions on loan loss provisioning. Consistent with my prediction, I find that banks' IT adoption level is positively associated with how quickly they announce their earnings after the fiscal quarter ends. The level of IT adoption is also negatively associated with both the likelihood of restatement and the likelihood of delaying SEC financial report filings.

Second, I test whether banks' IT adoption level is related to the likelihood of using credit analytical modeling that is expected to improve LLP timeliness (Bhat et al. 2019). I find that banks with a higher level of IT adoption are more likely to use credit analytical models, consistent with the reasoning that banks' intensive IT adoption improves the analysis and understanding of bank loan risks and potential losses, thereby increasing LLP timeliness.

This work contributes to the literature as follows. First, I contribute to the literature that attempts to understand the determinants of banks' LLP timeliness. For example, studies have found that borrower information sharing among banks (Balakrishnan and Ertan 2021), the use of different credit risk models (Bhat et al. 2019), and managers' reliance on low-quality information (Yang 2022) can affect LLP timeliness. In addition, Bushman, Hendricks, and Williams (2016) find that banks are likely to delay their loan loss provisioning when they face increased competition. Bhat, Lee, and Ryan (2021) document that LLP timeliness has substantial heterogeneity across loan types. My study complements and contrasts these papers by examining whether and how banks' IT adoption level affects their LLP timeliness. I also document novel evidence on the positive impact of IT adoption level on banks' internal information environment quality. These new findings are particularly relevant and informative to practitioners in banks, given that banks have increasingly invested in advanced IT in recent years (Modi et al. 2022).

Second, I contribute to the literature on technology adoption in banking.[5] Early studies focus on the role of IT in overall bank performance and provide mixed evidence (Berger 2003; Beccalli 2007; Koetter and Noth 2013). Recent studies document that banks with intensive IT investment performed better and increased credit supply during the 2008 financial crisis (Pierri and Timmer 2022) or following the COVID-19 outbreak (Branzoli, Rainone, and Supino 2021; Dadoukis, Fiaschetti, and Fusi 2021; Kwan et al. 2023). My research differs from these studies because I examine how IT affects the accounting process for loans (in particular, the timeliness in recognizing loan losses), which enhances the understanding of the impact of IT adoption in banking from a different viewpoint. For instance, my findings suggest that one potential mechanism through which IT investments improve banks' resilience in crises is the enhanced LLP timeliness (Beatty and Liao 2011). I further document some novel heterogeneity in the impact of IT in the banking industry; specifically, the LLP timeliness role of IT relies on the digital skills of staff and is more important when banks' business activities are geographically farther away from their headquarters.

[5] Section 2 provides more detailed discussion on this relevant literature.

The remainder of the paper is organized as follows. Section 2 discusses the related literature and the hypothesis development. Section 3 describes our sample and descriptive statistics. Section 4 presents the results of the empirical tests. Finally, Section 5 concludes.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1. Loan Loss Provisions

Loan loss provisioning—that is, accruing for loan losses——constitutes the primary component of banks' total accruals. It is fundamentally important to bank performance (see reviews by Beatty and Liao 2014; Bushman 2014). Recent studies have shown that the degree to which LLPs capture subsequent nonperforming loans (i.e., the timeliness of LLPs) effectively mitigates banks' pro-cyclical lending (Beatty and Liao 2011) and curbs excessive risk-taking (Bushman and Williams 2012, 2015).

2.1.1. Accounting Rules for LLP

Two frameworks guide banks' loan loss provisioning decisions: the expected loss model and the incurred loss model. Throughout my sample period, which spans from 2010 to 2019,[6] U.S. banks adopted the incurred loss model for their loan loss provisioning, in accordance with the U.S. Generally Accepted Accounting Principles (GAAP) Financial Accounting Standard (FAS) 5/FAS 114.[7] The incurred loss model mandates that banks set aside loss accruals only for loss contingencies that are incurred, probable of realization, and capable of reasonable estimation as of the financial statement date (Section 3.1.2 in Ryan 2012). Loan loss estimates should incorporate all observable data on losses, such as borrower loss of employment and a

[6] In the United States, large public banks switched to the current expected credit loss model of ASC 326 in 2020. For small public banks and private banks, the new rule becomes effective in 2023. For details, https://www.fasb.org/page/PageContent?pageId=/projects/recentlycompleted/credit-losses-transition.html&bcpath=tf&isCompletedProjectsPage=true, last accessed on June 6, 2023.

[7] FAS 5 provides impairment guidance for all receivables including loans, while FAS 114, adopted in May 1993, provides more specific guidance for accruing loan losses (see Beatty and Liao 2014).

decline in collateral values. These rules do not permit provisions to include expected credit losses.

2.1.2. Literature on Determinants of LLP Timeliness

Although accounting scholars have called for a better understanding of loan loss provisioning practices (Beatty and Liao 2014; Bushman 2014), a limited number of studies have been conducted regarding the determinants of banks' LLP timeliness. Bushman et al. (2016) find that banks tend to delay their loan loss provisioning when they face increased competition, suggesting that competition incentivizes bank managers to increase risk by relaxing loss recognition. Balakrishnan and Ertan (2021) find that following staggered initiations and coverage increases of public credit registries, affected banks increase the timeliness of their LLPs. This finding suggests that improvements in banks' information sets enhance their loan loss provisioning decisions. Yang (2022) finds that banks that originated more loans in areas with high mortgage fraud risk had greater inadequate loan loss allowances during the 2008 crisis. She interprets the findings as being consistent with the conjecture that bank managers' misunderstanding of the credit risks of mortgages explains banks' loan loss allowance inadequacy in the financial crisis.

In addition, Bhat et al. (2019) find that banks with greater reliance on a statistical analysis of historical loan performance exhibit timelier loan loss recognition in the non-crisis period, while banks that rely more on stress testing of credit losses to future adverse events are timelier in recognizing loan losses at the onset of the financial crisis. Using hand-collected data on allowance by loan type from banks' 10-K filings, Bhat et al. (2021) document that LLP timeliness varies greatly across loan types.

To the best of my knowledge, little evidence exists regarding the impact of banks' IT spending on their LLP timeliness.

2.2. Related Research on IT in Bank Industries

Early studies try to understand the impact of IT on bank overall performance. Berger (2003) reviews evidence on the economic effects of technological progress in the banking industry.[8] The evidence suggests that technology progress in banking has not only improved banks' cost efficiency and lending capacity, but has also increased consumer benefits by improving quality and variety of banking services. Beccalli (2007) examines whether investment in IT influences banks' performance in European countries over 1995–2000. The evidence is weak: while total IT investment has little effect on bank profitability or efficiency, investment in IT services from external providers (the acquisition of hardware and software) has a positive (negative) influence on banks' profit. Koetter and Noth (2013) use IT services data on 457 German savings banks from 1996 to 2006 and find that high IT use contributes to bank output (i.e., total factor productivity) and IT-augmented total factor productivity is positively related to bank market power.

To establish the causal impact of IT investment on banks' operations, recent studies take advantage of unexpected macro events. Pierri and Timmer (2022) find that banks with higher pre-crisis IT adoption experience fewer nonperforming loans and greater lending during the 2008–2009 financial crisis. Their loan-level analysis finds that higher-IT banks originated mortgages with better performance, indicating better borrower screening. They find no evidence suggesting that banks with high IT offload low-quality loans, change to different business models, or enhance monitoring.

A few studies exploit the recent COVID-19 pandemic as a negative shock to customer mobility restriction. Kwan et al. (2023) find that greater IT investment allowed banks to better serve their clients, increasing banks' deposits and small business credit supply. IT also

[8] A recent strand of literature focuses on the roles of the technology-based credit allocations ("FinTech"), including, for example, Berg et al. (2020); Chen, Wu, and Yang (2019); Di Maggio and Yao (2021); Fuster et al. (2019); Tang (2019); and Vallée and Zeng (2019).

enhanced customer review quality and improved bank performance during the pandemic (see also Dadoukis et al. 2021). Using Italian bank data, Core and De Marco (2023) find that greater IT investment enables banks to provide more loans to small businesses at cheaper rates and to lend more in areas where banks have no physical presence. Branzoli et al. (2021) further document that the positive relation between IT and bank lending following the pandemic outbreak in Italy is driven by both banks' ability to offer credit entirely online and banks' use of digital technologies for creditworthiness assessment.

Rather than examining the impact of IT investment on bank's performance and lending, He et al. (2021) study whether a bank's IT investment is determined by the information nature underlying its lending activities. They find that small business lending (a proxy for banks' demand of soft information production and transmission) drives banks' investment in communication IT, while personal loans (a proxy for banks' need to process hard information) explains banks' investment in software IT.

Taken together, existing studies have mainly focused on the implications of IT investment on the financial intermediation role of banks in credit markets, that is, whether IT enhances banks' ability to mitigate the information asymmetry that arises between depositors and borrowers. Nevertheless, little is known about the influence of banks' IT investment on their own internal information management and accounting policy decisions.

2.3. Hypothesis Development

I expect that banks' IT adoption is likely to facilitate timely recognition of loan losses for the following reasons. First, greater IT infrastructure could result in substantial improvements in banks' information sets, which could in turn enhance managers' estimates of LLPs and lead to timelier loan loss provisioning decisions (Balakrishnan and Ertan 2021; Yang 2022). Specifically, contemporary IT systems, known for their automation capabilities, streamline loan information processing (Dorantes et al. 2013; Pierri and Timmer 2022). For instance, when a loan officer approves a loan in a bank, the bank's IT systems activate to record the loan terms and borrower's credit information for accounting/finance, client relationship management, and credit risk management. This process not only minimizes the likelihood of human errors but also ensures that updated bank loan information is readily available when managers require it for loan loss recognition.

IT also improves banks' information sets by integrating all the credit information about borrowers and clients. Banks maintain vast amounts of client information from various industries and geographical locations over the years (Berger 2003). Prior studies suggest that modern IT systems can coordinate bank value-chain processes by integrating information from all the divisions and branches in a bank and storing such information in centralized databases (Barki and Pinsonneault 2005; Davenport 1998; Gattiker and Goodhue 2005). This coordination allows bank accountants to predict loan losses of a borrower more accurately by retrieving the cash flow information of the bank's clients in the same industry and region where the borrower is located.

Moreover, advanced IT allows banks with substantial IT investments to unleash new information from alternative unstructured data (big data) that can significantly enhance credit analysis (Berg et al. 2020). Realizing this potential, banks have been increasingly adopting such IT in recent years (e.g., Murawski 2019).

Second, IT enhances banks' internal controls, thereby improving the monitoring of loan loss recognition processes and reducing potential control risks for loan management, according to prior studies (Masli et al. 2010; Chapman and Kihn 2009). IT applications in banks include internal control monitoring technology that automates routine control tests, enhances risk assessments, evaluates and documents internal control processes, and communicates assurance activities by following generally accepted guidelines such as those from the Committee of Sponsoring Organization of the Treadway Committee (COSO 2009). For example, IT applications for internal control monitoring commonly incorporate features that include processes for upholding information integrity of different loan information, monitoring screens to provide alerts about irregularities of established loan policies, and maintaining segregation of duties for loan approval, assessment, and reporting. Internal controls for loan management and monitoring enable banks to avoid time-consuming checks for human errors with better effectiveness and to systematically implement mechanisms to effectively constrain any intentional misconduct during loan loss recognition processes.

Third, data analytical IT facilitates the use of credit analysis models when analyzing bank loans and forecasting loan losses. IT-based credit risk analytical tools in the financial industry can automatically incorporate effective credit analysis models for bank loan loss analysis (Deloitte 2019). Prior research finds that using credit risk models is positively related to LLP timeliness (Bhat et al. 2019). IT fosters a friendly environment for accessing credit risk models, given the availability of rich data sources. Moreover, the emergence of machine learning (ML) further enhances credit risk analysis with timely data (Wu et al. 2022). This trend is expected to significantly improve the timeliness of LLP.

However, intensive IT investment may not aid banks in the timely recognition of loan losses. First, investment in IT may create additional uncertainty in bank operations because IT investment is typically accompanied by uncertainty about its economic impact, technological complexity, rapid obsolescence, implementation challenges, and so on (Dewan and Ren 2011; Dewan et al. 2007). Such uncertainty may cause disruption to bank loan analyses for understanding bank loan losses. Second, a long-lasting concern regarding IT applications in banking is that hard information is easier to report and communicate than soft information, potentially causing banks to neglect the latter for loan analysis when IT applications are intensively used (Rajan et al. 2015). As banks' soft information is critical for loan assessment and analysis (Berger and Udell 2006), extensive IT adoption may hurt banks' timeliness in recognizing loan losses. I also note that the development of communication technology and the recent attempts of Fintech to gradually harden soft information (Liberti and Petersen 2019) may alleviate such a concern. Eventually, it remains empirically unclear whether the neglect of soft information can be completely overcome.

3. DATA

3.1. Sample Selection

To study how a bank's IT adoption affects its LLP timeliness, I obtain detailed annual IT budget information from the Harte Hanks Market Intelligence Computer Intelligence Technology (CI) database, which offers various IT-related information at the firm level. Recent banking studies have used this dataset, including He et al. (2022) and Kwan et al. (2023). This survey-based database is reliable: firms have strong incentives to truthfully report their IT budget records because they are in turn provided with professional advice and guidance for IT services in the future.

To estimate banks' LLP timeliness, I collect banks' quarterly financial information from Compustat Bank for the period from Q1 2011 to Q2 2022. I start in 2011 because the IT budget information is not available until 2010, and I use lagged IT data relative to banks' accounting information when estimating LLP timeliness. Moreover, as discussed in Section 3-*Measures of LLP Timeliness*, I construct LLP timeliness using a rolling window of the next 12 quarters. Thus, I am able to compute LLP timeliness for quarters up to Q3 2019.

After matching the data on LLP timeliness with CI database, I identify 359 U.S. public banks during the period from Q1 2011 to Q3 2019, consisting of 7,601 bank-quarter observations with control variables available in the benchmark regressions.

3.2. Measures of IT Adoption

The main independent variable, *Ln (Total IT/Emp)*, is equal to the natural logarithm of the total IT budget per employee. I take the logarithm transformation to reduce the right skewness in the data. One major strength of the CI database is that it provides us with a detailed decomposition of banks' IT investments in five categories: hardware, software, services, storage, and communication. Accordingly, I also compute the IT adoption measure for each of the five categories, and all are defined similarly to *Ln (Total IT/Emp).* For example, *Ln (Hardware IT/Emp)* is the natural logarithm of the annual IT budget on hardware scaled by total employees.

3.3. Measure of LLP Timeliness

I follow Beatty and Liao (2011) and define the timeliness of LLP as the additional explanatory power of future and current nonperforming loans in explaining the current loan loss provision beyond that of past nonperforming loans. In particular, I run the following two rolling regressions for each bank-quarter using its future 12 quarters' observations (current quarter inclusive), and then the timeliness measure is calculated as the difference of adjusted R^2 between two equations (Eqn.(2)-Eqn.(1)):

$$LLP_t = \alpha_0 + \alpha_1 \Delta NPL_{t-2} + \alpha_2 \Delta NPL_{t-1} + \alpha_3 Capital\ R1_t + \alpha_4 EBP_t + \varepsilon_t \tag{1}$$

$$LLP_t = \alpha_0 + \alpha_1 \Delta NPL_{t-2} + \alpha_2 \Delta NPL_{t-1} + \alpha_3 \Delta NPL_t + \alpha_4 \Delta NPL_{t+1} + \alpha_5 Capital\ R1_t + \alpha_6 EBP_t + \varepsilon_t \tag{2}$$

In the first equation, I include two-quarter-lagged (ΔNPL_{t-2}) and one-quarter-lagged change in nonperforming loans (ΔNPL_{t-1}), the beginning-of-quarter capital ratio ($Capital\ R1_t$), and earnings before provision (EBP_t) as the determinants of banks' LLP decision. In the second equation, I modify Eqn. (1) by adding the change in nonperforming loans in the current quarter (ΔNPL_t) and the next quarter (ΔNPL_{t+1}). I use the difference of adjusted R^2 between the two regressions as the timeliness measure. As the additional adjusted R^2 of Eqn. (2) over that of

Eqn. (1) indicates the extent to which loan loss provisioning reflects predicted future problem loans; a higher value indicates a timelier recognition of expected losses in a bank's loan provision decision.

3.4. Controls

To mitigate the concern that other characteristics could shape LLP timeliness, I include an assortment of controls that are commonly used in previous studies (e.g., Beatty and Liao 2011; Balakrishnan and Ertan 2021): firm size defined as the natural logarithm of total assets (*Ln(Total Assets)*), total deposits over total assets (*Deposit/Assets*), the ratio of total loans to assets (*Loans/Assets*), tier one risk-adjusted capital ratio (*Tier I Capital Ratio*), earnings before provision scaled by lagged loan amount (*Earnings before Provision*), and interest costs divided by total loans (*Interest Expense*). Importantly, *Tier I Capital Ratio* helps control for banks' incentives to manage capital through changing the timing of LLPs (Beatty, Chamberlain, and Magliolo 1995), while *Earnings before Provision* is used to control for banks' incentives to smooth earnings (Ahmed, Takeda, and Thomas 1999; Bushman and Williams 2012). As bank competition also affects LLP timeliness (Bushman et al. 2016), I include *Ln(1 plus # of Banks)*, defined as the natural log of one plus the total number of banks in a given state for each year. I winsorize continuous control variables at their 1st and 99th percentiles to reduce the impact of extreme outliers. Appendix A presents detailed definitions and data sources of all the variables used in this study.

Table 1 provides the summary statistics of the key variables. The dataset includes banks with their quarterly firm size ranging from 1,226 million dollars (25^{th} percentile) to 9,199 million dollars (75^{th} percentile), suggesting a broad coverage over different banks. For the main explanatory variables, the banks' average total IT budget for one employee in my sample corresponds to US$ 24,622. As for specific categories, all five IT categories take significant proportions of total IT budget. Other variables are consistent with the ones reported in previous literature.

4. EMPIRICAL RESULTS

4.1. Baseline

I estimate the impact of a bank's IT adoption on its timeliness of loan loss recognition by exploiting the following specification at bank-quarter level:

$$LLP\ Timeliness_{i,[q,q+11]} = \alpha_0 + \beta_0\ ln(IT/Emp)_{i,q-1} + \boldsymbol{\gamma X'_{i,q-1}} + FEs + \ \varepsilon_{i.q}, \qquad (3)$$

where i and q index bank and quarter, respectively. The dependent variable $LLP\ Timeliness_{i,[q,q+11]}$, the extent of timeliness in expected loss recognition, is calculated for each bank-quarter using two rolling regressions within a 12-quarter window. The independent variable of interest ($ln(IT/Emp)_{i,q-1}$) captures a bank's IT adoption level, calculated using the most recent IT data prior to the starting quarter when LLP is estimated. I expect a positive coefficient β_0, which means a higher IT adoption level would facilitate a bank to provide more timely LLPs.

Following previous literature (e.g., Beatty and Liao 2011; Balakrishnan and Ertan 2021), I include in $\boldsymbol{X'_{i,\,q-1}}$ a vector of controls: firm size, deposits-to-assets ratio, loans-to-assets ratio, tier one risk-adjusted capital ratio, earnings before provision, interest costs, as well as the number of banks across the same state. To mitigate any other unobserved time-invariant factors that might affect both IT and LLP timeliness, I include three sets of fixed effects. The regression includes business mode (6-digit GICS codes) and headquarter state fixed effects to control for unobservable time-invariant business operating and state characteristics. I also include year-quarter fixed effects to control for any contemporaneous correlations across observations in the same year-quarter. I use ordinary least squared regression (OLS) to estimate the model, with standard errors clustered at the bank level to account for heteroskedasticity and within-firm correlations.

Table 3 reports the regression results. I first investigate the effect of the total IT adoption level in columns (1) to (3). I start from column (1) without controls or any fixed effects. *Ln (Total IT/Emp)* loads positively and significantly at the 1% level, indicating that loan loss provision becomes timelier in banks with a higher IT adoption level. Then I extend the specification to include the three sets of fixed effects in column (2); I, in column (3), present the full model with the whole set of controls and fixed effects. The coefficient estimate on IT adoption measure remains statistically significant, and the size of the coefficient becomes even larger.

The economic magnitude is also meaningful. For example, in column (1), a one-standard-deviation increase in *Ln (Total IT/Emp)* is associated with a 25% [1×.02/.08] increase in the timeliness of loan loss provision relative to the sample average timeliness level.[9] These results are consistent with the hypothesis that greater investment in banks' IT technologies fosters more timely recognition of their loan loss provision.

Regarding the control variables, I observe that only *Ln(Total Assets) loads significantly, suggesting that* bigger banks are timelier at provisioning their expected loan loss.

I also replace total IT with each of the five specific categories of IT budget (*hardware*, *software*, *services*, *storage*, and *communication*) in Eqn. (3) and report the results in columns (4) to (8). The coefficient estimates across different IT types are similar in magnitude. It is not surprising given that all five categories of IT measures are highly correlated (as shown in Table 2), and this is also the reason why I am not able to include all five specific IT adoption measures together in one regression.

---

[9] As I use log-transformed IT per capita, one standard deviation change of Ln (Total IT/Emp), which is about 1, also means a 100% increase in IT budget per employee, i.e., from Eqn. (3), $\beta_0 = \frac{\partial y}{\partial \ln(x)} = \frac{\partial y}{\frac{\partial x}{x}}$. Such increase is feasible as the interquartile change of IT budget per employee in the sample is more than 200%.

4.2. Robustness Tests

4.2.1. IT Capital

Firstly I consider a stock-based IT measure: *Ln(Total IT capital/Emp)*. I define the total IT capital as the sum of the year one lagged IT budget, two-thirds of the year two lagged budget, and one-third of the year three lagged IT budget,[10] and then scale it by total employees and take the natural logarithm of the ratio. I also compute this stock-based measure for each IT category. The results in Panel A of Table 4 show that the prior inference is robust to the alternative IT measures.

4.2.2. Alternative Scalers

I scale the IT budget by other different variables, including total bank assets, bank market capitalization, and operating revenue. The results are reported in Panel B of Table 4. The positive relation between IT adoption and LLP timeliness is robust to alternative scalings.

4.2.3. Alternative SE Clusterings and Fixed Effects

I use more stringent fixed effects than the ones in the benchmark regressions. I incorporate state-by-quarter and business mode-by-quarter fixed effects, which allow me to account for any time-varying factors at state or bank operation levels. In addition, I cluster standard errors by both bank and quarter, accounting for any correlations within or across firms. I report the results in Panel C of Table 4, and I still find a significant positive relation between banks' IT adoption level and LLP timeliness.

4.2.4. Alternative measures of LLP Timeliness

First, I modify Eqn. (3) with an indicator variable for LLP timeliness as the dependent variable, which equals one if the value of the continuous timeliness measure is above the sample median (a timely recognition), and zero, otherwise. I estimate the model using OLS,

[10] This assumes a three-year value depletion period for IT capital (Lichtenberg 1995). A similar capitalization process is also used to capitalize past expenditure such as R&D capital in prior studies (e.g., Hirshleifer, Hsu, and Li 2013).

Probit, and Logit, respectively, and cluster standard errors by banks. The results, as reported in Table 4 Panel D, show a positive link between a bank's intensiveness on IT spending and the likelihood of its LLP being timely.

Second, I provide an alternative method of estimating LLP timeliness following the previous work (e.g., Bushman and Williams 2012):

$$\begin{aligned} LLP_{i,q} = {} & \alpha_0 + \alpha_1 \Delta NPL_{i,q-2} + \alpha_2 \Delta NPL_{i,q-1} + \alpha_3 \Delta NPL_{i,q} + \alpha_4 \Delta NPL_{i,q+1} \\ & + \beta_0\, ln(IT/Emp)_{i,q-1} + \beta_1\, \Delta NPL_{i,q-2} \times ln(IT/Emp)_{i,q-1} \\ & + \beta_2\, \Delta NPL_{i,q-1} \times ln(IT/Emp)_{i,q-1} + \beta_3\, \Delta NPL_{i,q} \times ln(IT/Emp)_{i,q-1} \\ & + \boldsymbol{\beta_4\, \Delta NPL_{i,q+1} \times ln(IT/Emp)_{i,q-1}} + \boldsymbol{\gamma X'_{i,q-1}} + FEs + \varepsilon_{i,q}, \end{aligned} \tag{4}$$

where i and q index bank and quarter, respectively, LLP is loan loss provisions divided by lagged total loans. ΔNPL is the quarterly change of non-performing loans. I use changes in non-performing loans in different quarters to predict a bank's loan loss provision. The coefficient on $\Delta NPL_{i,q+1}$ gauges the LLP timeliness in the sense that the current LLP already takes into consideration of future potential loan losses. Thus, the hypothesis implies a positive coefficient on the $\Delta NPL_{i,q+1} \times ln(IT/Emp)_{i,q-1}$: high IT level increases a bank's timeliness on LLPs. I include in this model the same set of controls and fixed effects as the baseline (Eqn. (3)). I cluster standard errors at the bank level.

Panel E of Table 4 reports the results. I exclude all controls in column (1), and then in column (2), I show the full specification. In both columns, I observe that the coefficients on the interaction term, $\Delta NPL_{i,q+1} \times ln(IT/Emp)_{i,q-1}$, are significantly positive, suggesting that higher IT investment promotes the predictive power of future change in non-performing loans for current loan loss provisioning. The finding is consistent with the main evidence.

4.3. IV Approach

The positive relation between IT adoption and LLP timeliness is subject to endogenous concerns. I alleviate this concern by using an IV. The IV is the number of data breach cases in local financial firms near a given bank. Data breaches are very costly to firms, leading to customer turnover, loss of reputation, forgone business opportunities, and litigation risks (e.g., Kamiya et al. 2021; Ponemon Institute 2022). It is plausible that local breach cases in the same industry increase managers' awareness of the importance of cybersecurity at the focal bank, incentivizing them to address cyber risk with increased investment in IT and cybersecurity.[11] This is consistent with Li et al.'s (2023) recent finding that when firms are aware of cyber risk, data breaches stimulate IT investment. Yet, it is difficult to argue that the occurrence of data breaches at other firms could directly influence the focal bank's decision on LLP timeliness. An example of the anecdotal evidence is that when Equifax disclosed a severe data breach incidence in 2017, a local bank in the same city, United Community Banks, began to disclose various IT projects in its 10K filings.[12] Furthermore, based on my calculation, the length of its discussion about security breaches increased by more than 100 percent from 2016 to 2018.

Table 5 reports the results of the instrumental variable analysis. The IV is the number of local breach incidents of banks in the past 10 years.[13] Following the convention (e.g., Coval and Moskowitz 1999, 2001), I define local banks as those located within 100 kilometers of the firm. The first stage regression is presented in column (1). The number of breach incidents in focal banks positively and significantly relates to the intensives of IT spending, satisfying the relevancy condition of the IV approach. I conduct an F-test of the weak instrumental variable. The results reject the null hypothesis that the IV explains little of banks' IT adoption level. I also conduct a Kleibergen-Paap rk LM test, which rejects the null hypothesis that the model is under-identified.

The two-stage least squares (2SLS) regression result is reported in column (2). I find a positive and statistically significant coefficient on *Ln(Total IT/Emp)*, consistent with my

---

[11] Using the data on data breach incidents, Ashraf (2022) shows that data breaches in peer firms are associated with a reduction in future internal control weaknesses for non-breached firms.

[12] See 2018 Form 10K, for example, https://www.sec.gov/Archives/edgar/data/857855/000085785519000021/ucbi1231201810-k.htm, last accessed on June 12, 2023.

[13] The results are robust if I alternatively use a 5-year or 3-year window.

previous baseline findings. The 2SLS coefficient estimate of *Ln(Total IT/Emp)* suggests a much larger positive effect of IT on LLP timeliness, compared with that of the OLS estimate. I note that this is likely due to the low incidence of cyberattacks, as reported in Table 1.[14] Bearing that in mind, let's consider the effect of one cyberattack. It makes the focal nonaffected banks, on average, increase IT budget per capita by 5.2%, leading to 31.5% [.052*.485/.08] improvement in LLP timeliness. Overall, the IV analysis mitigates the endogeneity concern of the positive relation between IT and LLP timeliness. Nevertheless, I caution readers about the external validity of this local average treatment effect.

4.4. Cross-sectional Tests

In this section, I investigate whether the effect of IT adoption varies across different groups of banks based on geographical dispersion between their headquarters and branches (Section 4.4.1), and on the bank-level digital human capital (Section 4.4.2).

4.4.1. Geographical Control Distance

If banks' IT adoption is positively related to LLP timeliness by improving their information sets, I expect that IT adoption will have a bigger effect on LLP timeliness among banks with their branches located farther away from the headquarters. Greater IT infrastructure enables banks to better integrate all the credit information about borrowers and clients across their branches (Berger 2003). Improvements in banks' information sets, in turn, help banks evaluate risks better, enhancing their loan loss provisioning decisions (Balakrishnan and Ertan 2021). As distance raises the cost of access to information, a high level of IT adoption should have a larger impact on banks whose branches are more distant from their headquarters.

Following Levine et al. (2020), I use the Summary of Deposits database to construct three measures of a bank's geographical dispersion: (1) the sum of the total distance (in kilometers)

[14] Consistent with this conjecture, the 2SLS coefficient estimate of *Ln(Total IT/Emp)* increases when I shorten the window that I use to compute the number of cyber attacks.

for each branch to the main office; (2) the deposit-weighted average distance (in kilometers) between a bank's headquarter location and its branches; and (3) the total number of branches. For each of the three measures, I create an indicator variable *D_Long* that is set to one if a bank's geographical dispersion is above the sample median and zero otherwise. I augment Eqn. (3) with *D_Long* and an interaction term between IT adoption and *D_Long*. I estimate the model using OLS and cluster the standard errors at banks. Table 6 reports our results.

Across the board, the coefficient on *Ln(Total IT/Emp)* × *D_Long* is positive and statistically significant. These results mean that the positive effect of IT adoption level on the timeliness of loan loss provisioning increases with dispersion. This finding is consistent with the view that IT spending facilitates banks' information management.[15]

4.4.2. Digital Human Capital

If banks' advanced IT adoption improves the analysis and understanding of their loan risks and losses, thereby enhancing timely LLPs, I expect that the effect of IT adoption in banking on LLP timeliness is greater when banks have a high level of digital human capital. This high level means that a high proportion of staff is capable of using IT analytical tools. Digital-capable employees are expected to better understand IT, specifically how processes, hardware, software, and networks interconnect in supporting the firm's financial reporting objectives (Abernathy et al. 2023).

I proxy the level of digital human capital in a bank by constructing an indicator using the data from a leading provider of labor market analytics (i.e., Revelio Labs).[16] *D_High*

[15] One may argue that this cross-sectional effect and even the overall effect of IT on LLP timeliness could be explained by the improved borrowers' quality because IT may allow banks to screen for high-quality borrowers, which is more useful for banks with geographically more dispersed business. To rule out this alternative explanation, I construct a loan quality indicator that is set to one for banks experiencing greater than the median value of the change of nonperformance loans over the next three years, zero otherwise. I add this dummy and its interaction with IT spending in our main regression Eqn. (3) (results available upon request). I find that the coefficient estimate on the interaction term is indistinguishable from zero, suggesting that this argument does not explain our results.

[16] The data have been used by several published papers (e.g., Li et al. 2022), and the data provider gathers unstructured data containing employees' online profiles and resumes from various websites and social media platforms such as LinkedIn, covering more than 380 million online profiles and resumes.

represents whether the ratio of employees with digital skills is greater than that of a median bank in our sample. Specifically, I construct four such ratios: (1) the ratio of finance/accounting employees with digital skills, which is the percentage of accounting and finance employees obtaining digital skills from their education; (2) the ratio of financial specialists with digital skills, which is the percentage of financial experts obtaining digital skills from their education; (3) the ratio of managers with digital skills, which is the percentage of managers who obtained their digital skills from their education;[17] and (4) the ratio of data analytics experts to total employees in the bank.[18] I augment Eqn. (3) with *D_High* and an interaction term between IT adoption and *D_High*. I estimate the model using OLS and cluster the standard errors at banks.

Table 7 shows that banks' IT adoption has a positive impact on LLP timeliness only in banks with adequate digital human capital. In contrast, for banks with inadequate digital human capital, the IT adoption level has little bearing on their loan loss timeliness. This finding holds for all the four measures of the fraction of bank employees with digital skills.

4.5. Additional Tests

I conduct two sets of analyses regarding the effects of banks' IT adoption leading to timely LLP recognition.

4.5.1. The Effects on Internal Information Quality

First, I test whether banks' internal information environment improves with their IT adoption level. A high IT adoption level should enhance a bank's ability to collect, process, and consume information within and across bank units, thereby improving its internal information quality. Improved internal information quality could facilitate managerial

---

[17] Specifically, I first obtain the detailed education information of each employee; and then I determine whether an employee has received an academic degree associated with digital skills by investigating this person's major and specialty. If this person's major is in information technology, statistics, or mathematics, I determine that the person has a digital skill. If this person has degrees from other fields, I follow prior studies (e.g., Chen and Srinivasan 2023; Acemoglu et al. 2022; Gao et al. 2023; Awyong et al. 2022) and search this person's specialty with a keyword list for digital skills.
[18] I classify whether an employee is a data analytical expert by using a 6-digit standard occupational classification code from the U.S. Bureau of Labor Statistics.

decision-making (e.g., Gallemore and Labro 2015), including managers' loan loss provisioning decisions.

To this end, I construct three proxies for banks' internal information quality.[19] The first measure, earnings announcement speed (*Speed*), is from Gallemore and Labro (2015); it is computed for each bank-quarter as the number of days between the end of the fiscal quarter and the earnings announcement date, divided by 90 and multiplied by negative one. A higher score corresponds to a higher quality of internal information. The second measure is an indicator variable, *Restatement*, that equals one for a bank in a given year that restates its financial statements according to the Audit Analytics Restatement database. A lower likelihood of restatements signifies a high-quality internal information environment. Our third measure is an indicator, *Delay*, that equals one for a bank failing to file the SEC reports (10K/10Q) on time at least once in a given year (e.g., Pincus et al. 2017). I obtain the banks' delay information from the Audit Analytics Late Filers database. *Delay* captures the internal efficiencies and information-integrated capability. The absence of any filing delay reveals high internal information quality.

Table 8 reports that IT spending, the proxy for banks' IT adoption level, is positively associated with how quickly banks announce their earnings after the fiscal quarter ends; IT spending is also negatively associated with both the likelihood of restatement and the likelihood of delaying SEC financial report filings. Consistent with the conjecture, the finding suggests that a high IT adoption level improves banks' internal information quality.

4.5.2. The Effects on Credit Risk Model Adoption

In the second analysis, I test whether banks' IT adoption level is related to the likelihood of using credit analytical modeling. In practice, banks engage in credit risk modeling to

[19] I also try to proxy the internal information quality by the management forecast accuracy (e.g., the one proposed in Gallemore and Labro 2015). However, I fail to do so given that a very limited number of banks make management forecasts captured by I/B/E/S database.

understand and manage their loan credit risks. According to Bhat et al. (2019), credit risk modeling increases the timeliness of banks' information about loan losses, thereby disciplining their LLPs. Therefore, I aim to test whether IT adoption enhances LLP timeliness by promoting the application of credit risk models with IT-based analytical tools.

Following Bhat et al. (2019), I create a bank-year panel by identifying two forms of credit risk modeling from banks' 10-K filings: statistical modeling of the drivers of past loan losses and stress testing of future loan losses under severely adverse scenarios. I create three dependent variables: (1) an indicator for whether a bank uses either form of credit risk modeling (*Credit Risk Analysis*); (2) an indicator for whether a bank uses statistical models only (*Statistical Model*); and (3) an indicator for whether a bank uses stress testings only (*Stress Testing*). I adopt the same set of control variables and fixed effects as in Eqn. (3), except that I replace quarter FEs by year FEs. I estimate the model using OLS and cluster standard errors by bank.

Table 9 reports that banks with a high level of IT adoption are more likely to use credit analytical models, which is mainly driven by a greater likelihood of using stress testing.

Together, the findings of the two analyses suggest that (1) improving internal information quality and (2) promoting the application of credit risk models are two possible channels through which banks' IT adoption enhances LLP timeliness.

5. CONCLUSIONS

In this study, I document that banks' IT adoption level is positively related to the timeliness of LLP. Using the number of past local banks' data breach cases as an IV for banks' IT adoption level, I conduct an IV analysis to support that IT adoption in banks can improve the timely recognition of LLP. This relation is more pronounced for banks with their business far from their headquarters and for banks with a high level of digital human capital, indicating a high proportion of staff capable of using IT analytical tools to understand bank loan credit risk.

I also find that the level of IT adoption in banks is positively related to several proxies for the quality of the banks' internal information environment, such as the speed of announcing earnings after the fiscal period ends, a lower likelihood of restatements, and a lower likelihood of delaying SEC financial report filing. These findings are consistent with the reasoning that banks' IT adoption improves the timeliness of LLP by enhancing internal information environment. Furthermore, IT adoption level of banks is positively associated with the use of credit risk models, which support the conjecture that banks' IT adoption enhances the timeliness of LLP by improving banks' understanding of bank loan credit risks.

This study suggests that the increasing use of IT in banks not only enhances bank performance during unique situations (e.g., crises) (e.g., Pierri and Timmer 2022; Dadoukis et al. 2021) but also enables banks to timely recognize LLP, as IT can improve both banks' internal information environment and their ability to analyze and understand loan credit risk. This extends the prior studies regarding the determinants of banks' LLP timeliness (e.g., Balakrishnan and Ertan 2021; Bhat et al. 2019). Future studies may survey banks to examine how they specifically utilize different types of IT applications for loan processes.

REFERENCES

Abernathy, J. L., J. P. Klaus, L. Le, and A. Masli. 2023. Does greater access to employees with information technology capability improve financial reporting quality? *Contemporary Accounting Research* (forthcoming).

Acemoglu, D., D. Autor, J. Hazell, and P. Restrepo. 2022. Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics* 40(S1):S293-S340.

Acharya, V. V., and S. G. Ryan. 2016. Banks' financial reporting and financial system stability. *Journal of Accounting Research* 54(2):277-340.

Ahmed, A. S., C. Takeda, and S. Thomas. 1999. Bank loan loss provisions: A reexamination of capital management, earnings management and signaling effects. *Journal of Accounting and Economics* 28(1): 1-25.

Awyong, A., Q. Cheng, T. Deng, and R. Wang. 2022. Digitalization, accounting jobs, and financial reporting quality. https://abfer.org/component/edocman/main-annual-conference/digitalization-accounting-jobs-and-financial-reporting-quality?Itemid=

Ashraf, M. 2022. The role of peer events in corporate governance: Evidence from data breaches. *The Accounting Review* 97 (2): 1–24.

Balakrishnan, K., and A. Ertan. 2021. Credit information sharing and loan loss recognition. *The Accounting Review* 96(4):27-50.

Barki, H., and A. Pinsonneault. 2005. A model of organizational integration, implementation effort, and performance. *Organization Science* 16(2):165-179.

Beatty, A., S. L. Chamberlain, and J. Magliolo. 1995. Managing financial reports of commercial banks: The influence of taxes, regulatory capital, and earnings. *Journal of Accounting Research* 33(2):231-261.

Beatty, A., and S. Liao. 2011. Do delays in expected loss recognition affect banks' willingness to lend? *Journal of Accounting and Economics* 52(1):1-20.

Beatty, A., and S. Liao. 2014. Financial accounting in the banking industry: A review of the empirical literature. *Journal of Accounting and Economics* 58(2-3):339-383.

Beccalli, E. 2007. Does IT investment improve bank performance? Evidence from Europe. *Journal of Banking and Finance* 31(7):2205-2230.

Berg, T., V. Burg, A. Gombović, and M. Puri. 2020. On the rise of fintechs: Credit scoring using digital footprints. *The Review of Financial Studies* 33(7):2845-2897.

Berger, A., S. Frame, and N. Miller. 2005. Credit scoring and the availability, price, and risk of small business credit. *Journal of Money, Credit and Banking* 37:191–222.

Berger, A. N. 2003. The economic effects of technological progress: Evidence from the banking industry. *Journal of Money, Credit and Banking* 35(2):141-176.

Berger, A. N., and G. F. Udell. 2006. A more complete conceptual framework for SME finance. *Journal of Banking and Finance* 30(11):2945-2966.

Bhat, G., J. A. Lee, and S. G. Ryan. 2021. Using loan loss indicators by loan type to sharpen the evaluation of banks' loan loss accruals. *Accounting Horizons* 35(3):69-91.

Bhat, G., S. G. Ryan, and D. Vyas. 2019. The implications of credit risk modeling for banks' loan loss provisions and loan-origination procyclicality. *Management Science* 65(5):2116-2141.

Bloom, N., L. Garicano, R. Sadun, and J. Van Reenen. 2014. The distinct effects of information technology and communication technology on firm organization. *Management Science* 60(12):2859-2885.

Boot, A., P. Hoffmann, L. Laeven, and L. Ratnovski. 2021. Fintech: What's old, what's new? *Journal of Financial Stability* 53:100836.

Branzoli, N., E. Rainone, and I. Supino. 2021. *The role of banks' technology adoption in credit markets during the pandemic*. https://ssrn.com/abstract=3878254 or http://dx.doi.org/10.2139/ssrn.3878254.

Bushman, R. M. 2014. Thoughts on financial accounting and the banking industry. *Journal of Accounting and Economics* 58(2-3):384-395.

Bushman, R. M., B. E. Hendricks, and C. D. Williams. 2016. Bank competition: Measurement, decision-making, and risk-taking. *Journal of Accounting Research* 54(3):777-826.

Bushman, R. M., and C. D. Williams. 2012. Accounting discretion, loan loss provisioning, and discipline of banks' risk-taking. *Journal of Accounting and Economics* 54(1):1-18.

Bushman, R. M., and C. D. Williams. 2015. Delayed expected loss recognition and the risk profile of banks. *Journal of Accounting Research* 53(3):511-553.

Carletti, E., S. Claessens, A. Fatás, and X. Vives. 2020. Post-Covid-19 world. Centre for Economic Policy Research.

Chapman, C. S., and L. A. Kihn. 2009. Information system integration, enabling control and performance. *Accounting, Organizations and Society* 34(2):151-169.

Chen, W., and S. Srinivasan. 2023. Going digital: Implications for firm value and performance. *The Review of Accounting Studies* (forthcoming).

Chen, M. A., Q. Wu, and B. Yang. 2019. How Valuable Is FinTech Innovation? *The Review of Financial Studies* 32 (5):2062-2106.

Claessens, S., J. Frost, G. Turner, and F. Zhu. 2018. Fintech credit markets around the world: size, drivers and policy issues. *BIS Quarterly Review* (September).

Committee of Sponsoring Organization of the Treadway Committee (COSO). 2009. Application Guidance on Monitoring Internal Control Systems, Vol. II. Durham, NC: COSO.

Core, F., and F. De Marco. 2023. Information technology and credit: Evidence from public guarantees. *Management Science* (forthcoming).

Coval, J. D., and T. J. Moskowitz. 1999. Home bias at home: Local equity preference in domestic portfolios. *Journal of Finance* 54(6):2045-2073.

Coval, J. D., and T. J. Moskowitz. 2001. The geography of investment: Informed trading and asset prices. *Journal of Political Economy* 109(4):811-841.

Dadoukis, A., M. Fiaschetti, and G. Fusi. 2021. IT adoption and bank performance during the Covid-19 pandemic. *Economics Letters* 204:109904.

Davenport, T. H. 1998. Putting the enterprise into the enterprise system. *Harvard Business Review* 76(4).

Deloitte. 2019. Credit risk measurement technology trend. Available at https://www2.deloitte.com/content/dam/Deloitte/lu/Documents/risk/lu-credit-risk-measurement-technology-trends.pdf

Dewan, S., and F. Ren. 2011. Information technology and firm boundaries: Impact on firm risk and return performance. *Information Systems Research* 22(2):369-388.

Dewan, S., C. Shi, and V. Gurbaxani. 2007. Investigating the risk-return relationship of information technology investment: Firm-level empirical analysis. *Management Science* 53(12):1829-1842.

Diamond, D. W., 1984. Financial intermediation and delegated monitoring. *The Review of Economic Studies* 51(3):393-414.

Di Maggio, M., and V. Yao. 2021. FinTech borrowers: Lax screening or cream-skimming? *The Review of Financial Studies* 34(10):4565-4618.

Dorantes, C. A., C. Li, G. F. Peters, and V. J. Richardson. 2013. The effect of enterprise systems implementation on the firm information environment. *Contemporary Accounting Research* 30(4):1427-1461.

Forman, C., A. Goldfarb, and S. Greenstein. 2012. The Internet and local wages: A puzzle. *American Economic Review* 102(1):556-575.

FSB. 2019. FinTech and market structure in financial services: Market developments and potential financial stability implications. Basel: Financial Stability Board.

Fuster, A., M. Plosser, P. Schnabl, and J. Vickery. 2019. The role of technology in mortgage lending. *The Review of Financial Studies* 32(5):1854-1899.

Gallemore, J., and E. Labro. 2015. The importance of the internal information environment for tax avoidance. *Journal of Accounting and Economics* 60(1):149-167.

Gao, J., K. Merkley, J. Pacelli, and J. H. Schroeder. 2023. Do internal control weaknesses affect firms' demand for accounting skills? Evidence from U.S. job postings. *The Accounting Review* 98 (3):203-228.

Gattiker, T. F., and D. L. Goodhue. 2005. What happens after ERP implementation: Understanding the impact of interdependence and differentiation on plant-level outcomes. *MIS Quarterly* 29(3):559-585.

He, Z., S. Jiang, D. Xu, and X. Yin. 2022. Investing in lending technology: IT spending in banking. NBER Working Paper: 30403.

Hirshleifer, D., P. H. Hsu, and D. M. Li. 2013. Innovative efficiency and stock returns. *Journal of Financial Economics* 107(3):632-654.

Kamiya, S., J. K. Kang, J. Kim, A. Milidonis, and R. M. Stulz. 2021. Risk management, firm reputation, and the impact of successful cyberattacks on target firms. *Journal of Financial Economics* 139(3):719-749.

Koetter, M., and F. Noth. 2013. IT use, productivity, and market power in banking. *Journal of Financial Stability* 9(4):695-704.

Kwan, A., C. Lin, V. Pursiainen, and M. Tai. 2023. Stress testing banks' digital capabilities: Evidence from the COVID-19 pandemic. *Journal of Financial and Quantitative Analysis* (forthcoming).

Levine, R., C. Lin, Q. Peng, and W. Xie. 2020. Communication within banking organizations and small business lending. *The Review of Financial Studies* 33(12):5750-5783.

Li, Q., B. Lourie, A. Nekrasov, and T. Shevlin. 2022. Employee turnover and firm performance: Large-sample archival evidence. *Management Science* 68(8):5667-5683.

Li, W., A. C. M. Leung, and W. T. Yue. 2023. Where is IT in information security? The interrelationship among IT investment, security awareness, and data breaches. *MIS Quarterly* 47(1):317-342.

Liberti, J. M., and M. A. Petersen. 2019. Information: Hard and soft. *Review of Corporate Finance Studies* 8(1):1-41.

Lichtenberg, F. R. 1995. The output contributions of computer equipment and personnel: A firm-level analysis. *Economics of Innovation and New Technology* 3(3/4):201-217.

Marquez, R., and R. Hauswald. 2003. Information technology and financial services competition. *Review of Financial Studies* 16:921–948.

Masli, A., G. F. Peters, V. J. Richardson, and J. M. Sanchez. 2010. Examining the potential benefits of internal control monitoring technology. *Accounting Review* 85(3):1001-1034.

Modi, K., N. Pierri, Y. Timmer, and M. S. M. Peria. 2022. The anatomy of banks' IT investments: Drivers and implications. IMF Working Papers, 2022(244).

Murawski, J. HSBC teams up with Element AI on big data. *Wall Street Journal*, June 18, 2019. https://www.wsj.com/articles/hsbc-teams-up-with-element-ai-on-big-data-11560850200

Nichols, D., J. Wahlen, and M. Wieland. 2009. Publicly-traded versus privately-held: Implications for bank profitability, growth risk, and accounting conservatism. *Review of Accounting Studies* 14:88-122.

Pierri, N., and Y. Timmer. 2022. The importance of technology in banking during a crisis. *Journal of Monetary Economics* 128:88-104.

Pincus, M., F. Tian, P. Wellmeyer, and S. X. Xu. 2017. Do clients' enterprise systems affect audit quality and efficiency? *Contemporary Accounting Research* 34(4):1975-2021.

Ponemon Institute. 2022. Cost of a data breach report. https://www.ibm.com/downloads/cas/3R8N1DZJ

Rajan, U., A. Seru, and V. Vig. 2015. The failure of models that predict failure: Distance, incentives, and defaults. *Journal of Financial Economics* 115(2):237-260.

Ryan, S. G. 2012. Financial reporting for financial instruments. *Foundations and Trends in Accounting* 6(3-4):187-354.

Tang, H. 2019. Peer-to-Peer Lenders Versus Banks: Substitutes or Complements? *The Review of Financial Studies* 32 (5):1900-1938.

U.S. Government Accountability Office. 2013. Financial institutions: Causes and consequences of recent bank failures. GAO-13-71.

Vallée, B., and Y. Zeng. 2019. Marketplace Lending: A New Banking Paradigm? *The Review of Financial Studies* 32 (5):1939-1982.

Wu, J., Z. Zhang, and S. X. Zhou. 2022. Credit rating prediction through supply chains: A machine learning approach. *Production and Operations Management* 31(4):1613-1629.

Yang, L. 2022. An information quality-based explanation for loan loss allowance inadequacy during the 2008 financial crisis. *Journal of Accounting and Economics* 73(1):101433.

APPENDIX A. VARIABLE DEFINITIONS

Variable	Definition	Source
Panel A: Measures for IT adoption		
Ln(Total IT/Emp)	A bank's total IT adoption level, calculated as the natural logarithm of the total annual IT budget scaled by the total number of employees.	CI
Ln(Hardware IT/Emp)	The natural logarithm of the annual IT budget on hardware scaled by the total number of employees.	CI
Ln(Software IT/Emp)	The natural logarithm of the annual IT budget on software scaled by the total number of employees.	CI
Ln(Services IT/Emp)	The natural logarithm of the annual IT budget on services scaled by the total number of employees.	CI
Ln(Storage IT/Emp)	The natural logarithm of the annual IT budget on storage scaled by the total number of employees.	CI
Ln(Communication IT/Emp)	The natural logarithm of the annual IT budget on communication scaled by the total number of employees.	CI
Ln(Total IT capital/Emp)	The natural logarithm of the annual IT capital scaled by the total number of employees. The IT budget capital for a given year is calculated as the sum of the year one lagged IT budget, two-thirds of the year two lagged budget, and one-third of the year three lagged IT budget.	CI
Ln(Total IT/Assets)	The natural logarithm of the total annual IT budget scaled by total assets.	CI
Ln(Total IT/Market Cap)	The natural logarithm of the total annual IT budget scaled by market capitalization.	CI
Ln(Total IT/Rev)	The natural logarithm of the total annual IT budget scaled by operating revenue.	CI
Panel B: LLP and LLP timeliness		
LLP Timeliness	The difference in the adjusted R2 (Eqn. (2)– Eqn. (1)) from the following two rolling regressions for each bank-quarter using the observations of next 12 quarters. A higher value indicates a timelier recognition. $LLP_t = \alpha_0 + \alpha_1 \Delta NPL_{t-2} + \alpha_2 \Delta NPL_{t-1} + \alpha_3 Capital\ R1_t + \alpha_4 EBP_t + \varepsilon_t$ (1) $LLP_t = \alpha_0 + \alpha_1 \Delta NPL_{t-2} + \alpha_2 \Delta NPL_{t-1} + \alpha_3 \Delta NPL_t + \alpha_4 \Delta NPL_{t+1} + \alpha_5 Capital\ R1_t + \alpha_6 EBP_t + \varepsilon_t$ (2)	Beatty and Liao (2011);Compustat
LLP Timeliness (0/1)	A dummy that equals one if the value of the continuous *LLP timeliness* is above the sample median (a timely recognition), and zero otherwise.	Beatty and Liao (2011);Compustat
LLP	Loan loss provision (pllq) divided by the lagged total loans (lntalq).	Compustat
ΔNPL	Change of non-performing loans (npatq) scaled by the lagged total loans (lntalq).	Compustat
Panel C: Controls		
Ln(Total Assets)	Firm size, defined as the natural logarithm of total assets (atq).	Compustat

Deposit/Assets	Deposit ratio, defined as the total deposits (dptcq) divided by total assets (atq).	Compustat
Loans/Assets	Loans to assets, defined as total loans (lntalq) divided by total assets (atq).	Compustat
Tier I Capital Ratio	Tier I risk-adjusted capital ratio (capr1q) at the beginning of the quarter, divided by 100.	Compustat
EBP	Earnings before provision (piq and pllq) scaled by lagged total loans (lntalq).	Compustat
Interest Expense	Interest costs (xintq) divided by total loans (lntalq).	Compustat
Ln(1 plus # of Banks)	The natural log of one plus total number of banks across a state-year.	SOD
Panel D: Others		
# of Local Breach Cases in Past 10Y	The number of data breach cases in local (within 100km) financial firms near a given bank in the past 10 years.	Audit Analytics
Speed	The number of days between the end of the fiscal quarter and the earnings announcement date, divided by 90 and multiplied by negative one. A higher score corresponds to a higher quality of internal information.	Gallemore and Labro (2015); IBES
Restatement	A dummy that equals one for years of a bank that have restatements.	Audit Analytics
Delay	A dummy equals one for a bank failing to file the SEC reports (10K/10Q) on time at least once in a given year.	Audit Analytics
Credit Risk Analysis	The indicator for whether a bank uses either form of credit risk modeling.	Bhat et al., (2019); 10K
Statistical Model	The indicator for whether a bank uses statistical models only.	Bhat et al., (2019); 10K
Stress Testing	The indicator for whether a bank uses stress tests only.	Bhat et al., (2019); 10K

APPENDIX B. TABLES

Table 1 Summary Statistics

This table presents the summary statistics for the key variables used in the analysis. All variables are defined in Appendix A.

Variable	Obs.	Mean	Std. Dev.	p25	p50	p75
Ln(Total IT/Emp)	7,601	9.743	1.016	9.302	9.938	10.465
Ln(Hardware IT/Emp)	7,601	7.946	0.814	7.537	8.115	8.440
Ln(Software IT/Emp)	7,601	8.624	1.191	8.263	8.855	9.457
Ln(Services IT/Emp)	7,601	8.669	1.361	8.344	9.027	9.594
Ln(Storage IT/Emp)	7,601	5.575	0.718	5.283	5.647	5.985
Ln(Communication IT/Emp)	7,601	7.188	0.886	6.626	7.267	7.834
Total IT/Emp	7,601	24622	18932	10958	20703	35066
Hardware IT/Emp	7,601	3599	2345	1875	3345	4627
Software IT/Emp	7,601	8863	7319	3878	7012	12800
Services IT/Emp	7,601	10036	8280	4205	8322	14670
Storage IT/Emp	7,601	319	191	197	283	397
Communication IT/Emp	7,601	1803	1390	754	1432	2524
LLP Timeliness	7,601	0.08	0.315	-0.135	0.02	0.240
Ln(Total Assets)	7,601	8.278	1.514	7.112	8.019	9.127
Deposit/Assets	7,601	0.788	0.069	0.753	0.799	0.835
Loans/Assets	7,601	0.656	0.114	0.599	0.672	0.736
Tier I Capital Ratio	7,601	0.13	0.028	0.111	0.126	0.144
EBP	7,601	0.006	0.003	0.004	0.006	0.007
Interest Expense	7,601	0.002	0.001	0.001	0.002	0.003
Ln(1 plus # of Banks)	7,601	4.923	0.86	4.543	5.13	5.403
# of breach cases in past 10Y	7,601	0.285	0.971	0	0	0
Speed	6,342	-0.829	0.635	-0.9	-0.8	-0.667
Restatement	2,911	0.036	0.186	0	0	0
Delay	2,911	0.013	0.116	0	0	0
Credit Risk Analysis	3,463	0.389	0.487	0	0	1
Statistical Model	3,463	0.055	0.228	0	0	0
Stress Testing	3,463	0.374	0.484	0	0	1

Table 2 Variable Correlations

This table presents Pearson correlations (*, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively). Panel A is for variables used in the baseline analysis; Panel B shows correlations among IT measures in different categories.

Panel A Correlations (p-values) among baseline variables

Variables	*LLP Timeliness*	*Ln(Total IT/Emp)*	*Ln(Total Assets)*	*Deposit/Assets*	*Loans/Assets*	*Tier I Capital Ratio*	*EBP*	*Interest Expense*	*Ln(1 plus # of Banks)*
LLP Timeliness	1.000								
Ln(Total IT/Emp)	0.0682***	1.000							
Ln(Total Assets)	0.1284***	0.046***	1.000						
Deposit/Assets	-0.068***	0.062***	-0.368***	1.000					
Loans/Assets	0.006	0.138***	-0.155***	0.121***	1.000				
Tier I Capital Ratio	-0.058***	-0.030***	-0.139***	0.004	-0.316***	1.000			
EBP	0.017	0.005	0.316***	-0.131***	-0.388***	0.176***	1.000		
Interest Expense	0.010	-0.295***	-0.124***	-0.402***	-0.168***	-0.059***	-0.060***	1.000	
Ln(1 plus # of Banks)	0.024**	-0.014	0.034***	0.057***	-0.034***	-0.084***	0.029**	-0.028**	1.000

Panel B Correlations (p-values) among IT categories

Variables	*Ln(Total IT/Emp)*	*Ln(Hardware IT/Emp)*	*Ln(Software IT/Emp)*	*Ln(Services IT/Emp)*	*Ln(Storage IT/Emp)*	*Ln(Commu-nication IT/Emp)*
Ln(Total IT/Emp)	1.000					
Ln(Hardware IT/Emp)	0.892***	1.000				
Ln(Software IT/Emp)	0.989***	0.832***	1.000			
Ln(Services IT/Emp)	0.971***	0.795***	0.990***	1.000		
Ln(Storage IT/Emp)	0.473***	0.759***	0.358***	0.268***	1.000	
Ln(Communication IT/Emp)	0.949***	0.878***	0.904***	0.861***	0.605***	1.000

Table 3 IT Adoption and LLP Timeliness: Baseline

The table reports the estimation results of how the banks' IT adoption level affects their LLP timeliness. The tests are at the bank-quarter level. The dependent variable, *LLP timeliness*, is calculated using rolling 12-quarter windows based on Beatty and Liao (2011). *Ln(Total IT/Emp)* is the natural logarithm of total IT budget divided by total employees in that bank. For a given quarter, I match with the most recent IT data prior to the starting quarter when LLP is estimated. Column (4) to (8) present the results when the total IT budget is divided into five specific categories: *hardware*, *software*, *services, storage*, and *communication,* and the corresponding independent variables are constructed respectively. I include business mode (6-digit GICS codes), headquarter state, as well as year-quarter Fes as control variables. All regressions are estimated using OLS, with standard errors clustered at the bank level and reported in the parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Dept. Var.	*LLP Timeliness*							
				By IT type				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Total IT/Emp)	0.021***	0.029***	0.032***					
	(0.006)	(0.011)	(0.011)					
Ln(Hardware IT/Emp)				0.031***				
				(0.011)				
Ln(Software IT/Emp)					0.032***			
					(0.011)			
Ln(Services IT/Emp)						0.032***		
						(0.011)		
Ln(Storage IT/Emp)							0.030***	
							(0.011)	
Ln(Communication IT/Emp)								0.031***
								(0.011)
Ln(Total Assets)			0.021**	0.021**	0.021**	0.021**	0.021**	0.021**
			(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Deposit/Assets			-0.209	-0.207	-0.208	-0.208	-0.208	-0.209
			(0.173)	(0.173)	(0.173)	(0.173)	(0.174)	(0.173)
Loans/Assets			-0.020	-0.021	-0.021	-0.020	-0.020	-0.020
			(0.088)	(0.088)	(0.088)	(0.088)	(0.088)	(0.088)
Tier I Capital Ratio			-0.534	-0.529	-0.535	-0.533	-0.532	-0.531
			(0.328)	(0.329)	(0.327)	(0.328)	(0.328)	(0.329)
EBP			-2.593	-2.614	-2.641	-2.553	-2.505	-2.564
			(2.963)	(2.968)	(2.957)	(2.965)	(2.962)	(2.965)
Interest Expense			-2.616	-2.598	-2.603	-2.598	-2.593	-2.580

			(10.124)	(10.114)	(10.124)	(10.123)	(10.136)	(10.131)
Ln(1 plus # of Banks)			0.095	0.095	0.095	0.093	0.093	0.093
			(0.152)	(0.152)	(0.151)	(0.151)	(0.152)	(0.152)
Observations	7,601	7,601	7,601	7,601	7,601	7,601	7,601	7,601
Business mode FE		Y	Y	Y	Y	Y	Y	Y
State FE		Y	Y	Y	Y	Y	Y	Y
Year-qtr FE		Y	Y	Y	Y	Y	Y	Y
Adj. R^2	0.005	0.018	0.033	0.033	0.033	0.033	0.033	0.033

Table 4 IT Adoption and LLP Timeliness: Robustness

The table reports the results of various robustness tests on the effect of IT adoption on LLP timeliness. Panel A reports the regression results by using IT capital as an alternative IT adoption measure. For a given year, IT $Capital_t$=1/3×IT $budget_{t-3}$+2/3×IT $budget_{t-2}$+1×IT $budget_{t-1}$.. Panel B reports the regression results by using the alternative scalers of IT adoption, including total assets, market capitalization, and operating revenue; In Panel C, I include alternative fixed effects and cluster standard errors in different ways; I consider *LLP timeliness* as a dichotomy variable in Panel D; Finally, Panel E presents an alternative measure of LLP timeliness (Bushman and Williams, 2012):

$$\begin{aligned}LLP_{i,q} = {} & \alpha_0 + \alpha_1 \Delta NPL_{i,q-2} + \alpha_2 \Delta NPL_{i,q-1} + \alpha_3 \Delta NPL_{i,q} + \alpha_4 \Delta NPL_{i,q+1} + \beta_0\, ln(IT/Emp)_{i,q-1} \\ & + \beta_1\, \Delta NPL_{i,q-2} \times ln(IT/Emp)_{i,q-1} + \beta_2\, \Delta NPL_{i,q-1} \times ln(IT/Emp)_{i,q-1} \\ & + \beta_3\, \Delta NPL_{i,q} \times ln(IT/Emp)_{i,q-1} + \boldsymbol{\beta_4\, \Delta NPL_{i,q+1} \times ln(IT/Emp)_{i,q-1}} + \boldsymbol{\gamma X'_{i,q-1}} + FEs \\ & + \varepsilon_{i,q}\end{aligned}$$

I use time series of change in non-performing loans and their interactions with IT adoption level to predict a bank's loan loss provision. All variables used are defined in the Appendix A. All standard errors are clustered at the bank level, except Panel C. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: IT Capitalization

	LLP Timeliness					
		By IT type				
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Total IT capital/Emp)	0.030***					
	(0.011)					
Ln(Hardware IT capital/Emp)		0.027**				
		(0.011)				
Ln(Software IT capital/Emp)			0.029***			
			(0.010)			
Ln(Services IT capital/Emp)				0.029***		
				(0.010)		
Ln(Storage IT capital/Emp)					0.025**	
					(0.011)	
Ln(Communication IT capital/Emp)						0.029***
						(0.011)
Ln(Total Assets)	0.021**	0.021**	0.022**	0.022**	0.021**	0.021**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Deposit/Assets	-0.211	-0.212	-0.209	-0.208	-0.210	-0.212
	(0.174)	(0.174)	(0.174)	(0.174)	(0.174)	(0.174)
Loans/Assets	-0.016	-0.017	-0.017	-0.016	-0.015	-0.016
	(0.088)	(0.088)	(0.088)	(0.089)	(0.088)	(0.088)
Tier I Capital Ratio	-0.548*	-0.543*	-0.549*	-0.545*	-0.532	-0.540
	(0.328)	(0.328)	(0.327)	(0.329)	(0.328)	(0.328)
EBP	-2.611	-2.580	-2.688	-2.620	-2.459	-2.521
	(2.949)	(2.960)	(2.942)	(2.947)	(2.958)	(2.957)
Interest Expense	-2.524	-2.550	-2.591	-2.686	-2.119	-2.228
	(10.145)	(10.128)	(10.138)	(10.126)	(10.183)	(10.175)
Ln(1 plus # of Banks)	0.083	0.084	0.080	0.077	0.091	0.089
	(0.150)	(0.150)	(0.150)	(0.150)	(0.151)	(0.150)
Observations	7,601	7,601	7,601	7,601	7,601	7,601
Business mode FE	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y
Year-qtr FE	Y	Y	Y	Y	Y	Y
Adj. R^2	0.033	0.032	0.033	0.033	0.032	0.032

Table 4-Panel B: Alternative Scalers

Dept. Var.	LLP Timeliness		
	(1)	(2)	(3)
Ln(Total IT/Assets)	0.026**		
	(0.011)		
Ln(Total IT/Market Cap)		0.021**	
		(0.009)	
Ln(Total IT/Rev)			0.024**
			(0.011)
Ln(Total Assets)	0.024***	0.024***	0.024***
	(0.009)	(0.009)	(0.009)
Deposit/Assets	-0.212	-0.230	-0.215
	(0.173)	(0.174)	(0.174)
Loans/Assets	-0.004	0.011	0.005
	(0.088)	(0.086)	(0.089)
Tier I Capital Ratio	-0.520	-0.417	-0.510
	(0.327)	(0.334)	(0.330)
EBP	-2.128	-0.753	-1.958
	(2.965)	(2.983)	(2.965)
Interest Expense	0.105	-3.790	-0.048
	(10.224)	(10.084)	(10.285)
Ln(1 plus # of Banks)	0.092	0.075	0.095
	(0.151)	(0.152)	(0.151)
Observations	7,601	7,601	7,601
Business mode FE	Y	Y	Y
State FE	Y	Y	Y
Year-qtr FE	Y	Y	Y
Adj. R^2	0.032	0.032	0.031

Table 4-Panel C: Alternative FEs and Clustering Groups

Dept. Var.	LLP Timeliness	
	(1)	(2)
Ln(Total IT/Emp)	0.026**	0.032***
	(0.013)	(0.011)
Ln(Total Assets)	0.019*	0.021**
	(0.010)	(0.009)
Deposit/Assets	-0.200	-0.209
	(0.200)	(0.178)
Loans/Assets	-0.011	-0.020
	(0.101)	(0.093)
Tier I Capital Ratio	-0.625*	-0.534
	(0.373)	(0.334)
EBP	-0.664	-2.593
	(3.561)	(2.917)
Interest Expense	-3.576	-2.616
	(12.013)	(9.906)
Ln(1 plus # of Banks)		0.095
		(0.157)
Observations	7,264	7,601
Business mode FE		Y

State FE		Y
Year-qtr FE		Y
Business mode by Year-qtr FE	Y	
State by Year-qtr FE	Y	
Cluster at bank	Y	Y
Cluster at Year-qtr		Y
Adj. R^2	0.008	0.033

Table 4-Panel D: LLP Dichotomy Timeliness Measure

Dept. Var.	*LLP Timeliness (0/1)*		
	OLS	Probit	Logit
	(1)	(2)	(3)
Ln(Total IT/Emp)	0.033**	0.086**	0.138**
	(0.015)	(0.039)	(0.062)
Ln(Total Assets)	0.019*	0.048*	0.078*
	(0.011)	(0.029)	(0.047)
Deposit/Assets	-0.249	-0.677	-1.066
	(0.205)	(0.530)	(0.850)
Loans/Assets	-0.121	-0.310	-0.493
	(0.109)	(0.282)	(0.451)
Tier I Capital Ratio	-0.786	-2.030*	-3.246
	(0.482)	(1.229)	(1.985)
EBP	-0.819	-2.011	-3.348
	(3.909)	(10.094)	(16.225)
Interest Expense	-2.609	-7.343	-10.977
	(13.366)	(34.229)	(55.098)
Ln(1 plus # of Banks)	0.030	0.076	0.128
	(0.215)	(0.558)	(0.896)
Observations	7,601	7,597	7,597
Business mode FE	Y	Y	Y
State FE	Y	Y	Y
Year-qtr FE	Y	Y	Y
Adj. R^2/Pseudo R^2	0.020	0.023	0.023

Table 4-Panel E: Bushman and Williams (2012)'s LLP timeliness measure

Dept. Var.	*LLP*	
	(1)	(2)
ΔNPL_{t+1} ×*Ln(Total IT/Emp)*	0.063***	0.062***
	(0.023)	(0.023)
ΔNPL_{t} ×*Ln(Total IT/Emp)*	0.022	0.020
	(0.024)	(0.024)
ΔNPL_{t-1}×*Ln(Total IT/Emp)*	0.011	0.006
	(0.021)	(0.020)
ΔNPL_{t-2} ×*Ln(Total IT/Emp)*	-0.004	-0.006
	(0.021)	(0.021)
Ln(Total IT/Emp)	-0.069*	-0.056
	(0.039)	(0.039)
ΔNPL_{t+1}	-0.015	-0.013
	(0.026)	(0.028)
ΔNPL_{t}	0.040*	0.039*
	(0.024)	(0.023)
ΔNPL_{t-1}	0.065***	0.059***
	(0.020)	(0.020)
ΔNPL_{t-2}	0.109***	0.098***
	(0.018)	(0.018)
Ln(Total Assets)		0.070**
		(0.029)
Deposit/Assets		1.520**
		(0.619)
Loans/Assets		0.531
		(0.326)
Tier I Capital Ratio		-3.109***
		(1.108)
EBP		31.800
		(21.925)
Interest Expense		146.752***
		(44.616)
Ln(1 plus # of Banks)		2.918***
		(0.548)
Observations	7,587	7,587
Business mode FE	Y	Y
State FE	Y	Y
Year-qtr FE	Y	Y
Adj. R^2	0.278	0.305

Table 5 Instruments

The table reports the results of the instrumental variable analysis of the relation between IT adoption and banks' LLP timeliness. I instrument bank IT investment using the number of local data breach cases of other financial firms within 100 km of the focal bank in the past 10 years. Columns (1) and (2) report the regression results of the first stage and second stage regressions, respectively. Standard errors are clustered at the bank level and reported in the parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Dept. Var.	(1) First-Stage	(2) 2SLS
	Ln(Total IT/Emp)	*LLP Timeliness*
# of Local Breach Cases in Past 10 Years	0.052***	
	(0.014)	
Ln(Total IT/Emp)		0.485**
		(0.209)
Ln(Total Assets)	-0.036	0.025
	(0.027)	(0.024)
Deposit/Assets	-0.308	-0.205
	(0.487)	(0.267)
Loans/Assets	0.041	-0.036
	(0.320)	(0.165)
Tier I Capital Ratio	0.828	-1.084
	(0.713)	(0.442)
EBP	8.900	-8.182
	(9.433)	(7.228)
Interest Expense	-39.474	5.324
	(31.060)	(18.645)
Ln(1 plus # of Banks)	0.078	0.160
	(0.060)	(0.212)
Observations	7,601	7,601
Business mode FE	Y	Y
State FE	Y	Y
Year-qtr FE	Y	Y
F: 11.31***		
Montiel-Pflueger robust weak instrument test F: 11.26**		
Kleibergen-Paap rk LM statistic: 3.065*		

Table 6 Heterogeneous Effects by Geographical Control Distance

This table reports the cross-sectional tests on banks' geographical controls distance. I collect banks' main office as well as their branches data from the Summary of Deposits (SOD) database. I construct three measures: sum of the total distance (in kilometers) for each branch to the main office in column (1); deposit-weighted distance (in kilometers) for each branch to their main office in column (2); and the total number of branches in column (3). *D_Long* equals one if the value of the measure is greater than the median value in each sample, and 0 otherwise. In these tests, I also decentralize *Ln(Total IT/Emp)* in order to properly interpret the interaction term and related main effects. The regressions are estimated using OLS, with standard errors clustered at the bank level and reported in the parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Dept. Var:	*LLP Timeliness*		
	(1) Total distance	(2) Deposit-weighed distance	(3) Number of branches
Ln(Total IT/Emp)* × *D_Long	0.030***	0.028**	0.030**
	(0.011)	(0.012)	(0.012)
Ln(Total IT/Emp)	0.019	0.018	0.019*
	(0.012)	(0.012)	(0.011)
D_Long	-0.006	0.008	-0.016
	(0.022)	(0.024)	(0.022)
Ln(Total Assets)	0.022**	0.019*	0.023**
	(0.010)	(0.010)	(0.010)
Deposit/Assets	-0.213	-0.213	-0.219
	(0.173)	(0.174)	(0.173)
Loans/Assets	-0.016	-0.021	-0.024
	(0.088)	(0.089)	(0.088)
Tier I Capital Ratio	-0.520	-0.535	-0.511
	(0.330)	(0.327)	(0.329)
EBP	-2.539	-2.525	-2.558
	(2.976)	(2.984)	(2.968)
Interest Expense	-4.056	-3.381	-5.650
	(9.967)	(10.030)	(10.162)
Ln(1 plus # of Banks)	0.099	0.102	0.092
	(0.150)	(0.151)	(0.152)
Observations	7,601	7,601	7,601
Business mode FE	Y	Y	Y
State FE	Y	Y	Y
Year-qtr FE	Y	Y	Y
Adj. R^2	0.035	0.035	0.035

Table 7 Heterogeneous Effects by IT-related Human Capital

This table reports the cross-sectional tests on banks' intensity of digital talents. Specifically, I consider the ratio of finance/acct employees with digital skills in column (1), the ratio of financial specialists with digital skills in column (2), the ratio of managers with digital skills in column (3), and the ratio of data analytics experts to total employees in the bank in column (4). If the ratio value is above the sample median, I make *D_High Ratio* as one to indicate it. I also decentralize *Ln(Total IT/Emp)*. All regressions are estimated using OLS, with standard errors clustered at the bank level and reported in the parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Dept. Var:	*LLP Timeliness*			
	(1) Finance/Acct	(2) Financial specialists	(3) Managers	(4) Data experts
Ln(Total IT/Emp)* × *D_High Ratio	0.038**	0.044***	0.038***	0.039**
	(0.017)	(0.016)	(0.014)	(0.016)
Ln(Total IT/Emp)	0.011	0.005	0.015	0.015
	(0.020)	(0.019)	(0.016)	(0.017)
D_High Ratio	-0.008	0.002	0.020	-0.015
	(0.021)	(0.021)	(0.021)	(0.026)
Ln(Total Assets)	0.028**	0.026**	0.023*	0.029**
	(0.013)	(0.013)	(0.013)	(0.014)
Deposit/Assets	-0.068	-0.072	-0.088	-0.079
	(0.246)	(0.243)	(0.244)	(0.247)
Loans/Assets	-0.101	-0.104	-0.105	-0.102
	(0.121)	(0.120)	(0.122)	(0.121)
Tier I Capital Ratio	-0.765	-0.706	-0.782	-0.802
	(0.505)	(0.504)	(0.496)	(0.512)
EBP	0.175	0.175	-0.198	0.067
	(4.203)	(4.183)	(4.176)	(4.240)
Interest Expense	-10.985	-10.847	-13.298	-14.591
	(13.910)	(13.843)	(13.685)	(13.963)
Ln(1 plus # of Banks)	0.247	0.237	0.254	0.251
	(0.199)	(0.205)	(0.200)	(0.200)
Observations	5,204	5,204	5,204	5,204
Business mode FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Year-qtr FE	Y	Y	Y	Y
Adj. R^2	0.056	0.057	0.057	0.057

Table 8 Additional Tests: The Effects on Internal Information Quality

This table presents the results of the examination of the relation between banks' IT adoption and their internal information quality. I construct three measures to gauge a firm's internal information quality. I follow Gallemore and Labro's (2015) method and construct a quarterly earnings announcement speed (*Speed*), which is computed as the number of days between the end of the fiscal quarter and the earnings announcement date, divided by 90 and multiplied by negative one. A higher score corresponds to a higher quality in internal information. In column (2), *Restatement* equals one if the bank has restatements captured by the Audit Analytics Restatement database in a given year, and one otherwise. In column (3), *Delay* equals one if a bank failed to file the SEC reports (10K/10Q) on time at least once during a year. The absence of either restatements or filling delays signals the high quality of internal information. All standard errors are clustered at the bank level and reported in the parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Dept. Var.	*Speed*	*Restatement*	*Delay*
	(1)	(2)	(3)
Ln(Total IT/Emp)	0.053**	-0.019**	-0.015*
	(0.023)	(0.009)	(0.009)
Ln(Total Assets)	0.063***	0.007*	-0.005**
	(0.009)	(0.004)	(0.002)
Deposit/Assets	-0.150	0.027	-0.025
	(0.219)	(0.076)	(0.056)
Loans/Assets	0.166	-0.013	-0.041
	(0.117)	(0.033)	(0.026)
Tier I Capital Ratio	1.412***	-0.197	-0.132
	(0.387)	(0.164)	(0.120)
EBP	14.072***	-0.739*	-0.342
	(4.999)	(0.447)	(0.369)
Interest Expense	-15.673	2.264*	1.112
	(11.567)	(1.162)	(0.825)
Ln(1 plus # of Banks)	-0.363	-0.001	0.000
	(0.543)	(0.013)	(0.004)
Observations	6,342	2,911	2,911
Business mode FE	Y	Y	Y
State FE	Y	Y	Y
Year-qtr FE	Y		
Year FE		Y	Y
Adj. R^2	0.075	0.017	0.017

Table 9 Additional Tests: The Effects on Application of Credit Risk Models

This table presents the results of the examination of the relation between banks' IT adoption and the likelihood of using credit analytical modeling. Following Bhat et al. (2019), I identify two forms of credit risk modeling from banks' 10-K filings: statistical modeling and stress testing. I create three dependent variables: (1) the indicator for whether a bank uses either form of credit risk modeling (Credit Risk Analysis); (2) the indicator for whether a bank uses statistical models only (Statistical Model); and (3) the indicator for whether a bank uses stress tastings only (Stress Testing). I use OLS and alll standard errors are clustered at the bank level and reported in the parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Dept. Var.	*Credit Risk Analysis*	*Statistical Model*	*Stress Testing*
	(1)	(2)	(3)
Ln(Total IT/Emp)	0.037**	-0.003	0.039**
	(0.018)	(0.006)	(0.018)
Ln(Total Assets)	0.118***	0.033***	0.121***
	(0.010)	(0.009)	(0.010)
Deposit/Assets	0.227	0.071	0.257
	(0.248)	(0.144)	(0.250)
Loans/Assets	-0.259	-0.205**	-0.233
	(0.157)	(0.089)	(0.153)
Tier I Capital Ratio	-0.154	0.033	-0.162
	(0.376)	(0.110)	(0.376)
EBP	-1.681**	-0.447	-1.661*
	(0.839)	(0.615)	(0.852)
Interest Expense	-1.067	0.046	0.344
	(2.375)	(0.910)	(2.365)
Ln(1 plus # of Banks)	-0.011	-0.028**	-0.009
	(0.019)	(0.014)	(0.019)
Observations	3,463	3,463	3,463
Business mode FE	Y	Y	Y
State FE	Y	Y	Y
Year FE	Y	Y	Y
Adj. R^2	0.219	0.232	0.221