Fintech, Technology Engagement, and Bank Performance

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Abstract

As technology reshapes the banking landscape, this study first explores how digital payment platforms affect profitability and risk-taking behavior in the Chinese banking sector. By employing both fixed effects model and system generalized method of moments (Sys-GMM) on a dataset covering 1,747 observations from 2011 to 2020, our findings highlight that digital payment platforms have a consistently adverse impact on the risk-taking behaviors of Chinese commercial banks, a result that remains robust across different explanatory factors considered. Moreover, the study shows that, although not highly robust, digital payment platforms harm the profitability of urban and rural commercial banks, suggesting a developmental disadvantage for urban and rural banks. Additionally, the implementation of regulatory policies and the occurrence of COVID-19, transform the impact on profitability into a positive one. The inhibitory impact on risk-taking becomes more pronounced under these circumstances.

Against the impact from technology advancements, incumbent banks are actively pursuing diverse technological engagement. Subsequently, this study investigates whether technology-driven M&A transactions of commercial banks, influence their opacity in a Japanese context. We examined 461 transactions from April 1999 to March 2022, employing both propensity score matching (PSM) and differences-in-differences PSM (DID-PSM) within the Rubin Causal Model. The results offer evidence that technology-driven M&As are related to reduced bank opacity, a consistent finding across different econometric methods, and outcome variables. Moreover, this attenuation effect is more prominent in the case of foreign technology-driven M&As. Additionally, the research explores the effects of these transactions on stock price synchronicity and risk composition, conditioning on the inverse relationship between bank opacity and stock price informativeness. The analysis suggests that banks engaged in technology-driven M&As undergo

decreased stock price synchronicity and systematic risk.

The obtained software and technology-related products through technology engagement such as M&As, are documented as intangible assets on the balance sheet while serving as a means of embracing digital transformations. This study also furnishes empirical evidence regarding the connection between bank efficiency and identifiable intangibles in a multinational analysis. Our dataset includes information from 624 commercial banks spanning four regions, compassing 30 countries: the European Union (EU, 27 countries), the United States (US), Japan (JP), and Mainland China (CN). Covering a 10-year period from 2012 to 2021, this dataset comprises a total of 5,277 observations. We initiated the analysis by applying a new stochastic meta-frontier analysis (Meta-SFA) that predicts individual efficiency scores within a single country, while estimates meta-efficiency scores within a group of countries with idiosyncratic term included into estimation to break down the national barriers. To address the reverse causality between efficiency and competitiveness, instrumental variables are introduced into the estimation using a two-stage least squares (2SLS) approach and the generalized method of moments (GMM). Estimated results suggest that intangible assets boost bank efficiency, especially in meta-efficiency improvement. Additionally, controlling the differentiation among incumbent commercial banks due to national fintech development, intangible assets play a crucial role in fostering perfect competition and hastening efficiency convergence.

In practice, banks can establish collaborations with financial technology to boost digital transformation through active technology engagement, which also contributes to bank transparency and stock market stability. Nevertheless, rural commercial banks and those in developing regions may face a disadvantage compared to counterparts involved in strategic collaborations, addressing the necessary for additional governmental support. A more comprehensive accounting disclosure of technology-related assets is also vital to strengthen external

monitoring and facilitate accurate evaluations.

Keyword Digital payment platforms, Technology-driven M&As, Intangible assets, Bank profitability, Bank risk-taking, Bank opacity, Bank efficiency, Stock price synchronicity, Stock risk composition

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Contents

1 Introduction

In recent years, significant advancements have been observed in the extent of financial inclusion, which is largely attributable to technological innovations. This amalgamation of financial services and technology, commonly referred to as fintech by the Financial Stability Board (FSB, 2017), is presenting new challenges for conventional banking systems, because the development of innovative financial services leading to novel business models, applications, processes, and products. As financial technologies continue to ascend, their impacts on the banking sector and the responses from the banking industry such as investment behavior, have become well-established research questions (Röder & Walter, 2019).

As for their impacts on the banking sector, drawing on previous research, two perspectives on the relationship between technology firms and established banks emerge: the perspective of complementary and collaborative innovations versus that of substituting and disruptive innovations (Drasch et al., 2018). The viewpoint emphasizing complementarity and collaboration is supported by enhanced operating efficiency, competitive capability, and corporate performance resulting from knowledge synergies (Austin & Dunham, 2022; Cappa et al., 2022; Dranev et al., 2019; Kogut & Zander, 1992; Ma & Liu, 2017). The digital transformation in the financial industry yields a substantial volume of data for analysis within the banking sector. This process cuts down the cost of acquiring information while simultaneously enhancing market transparency and improving information symmetry (Chen et al., 2021; Yao & Song, 2021), which also benefits bank profitability and risk-taking behavior (Dong et al., 2020; Wang et al., 2021). Furthermore, the expansion of the investment opportunity set driven by technological advancements facilitates risk diversification.

Conversely, the substitution and disruption effect can originate from the challenges and intrinsic riskiness of high-tech industry (Cappa et al., 2022; Dranev et al., 2019; McCarthy & Aalbers, 2016). Owing to the slowdown in card usage and the wealth management resulting from financial technology firms, banks are grappling with challenges in their interest income and non-interest income. They may find it necessary to adjust their risk-taking tolerance for grinding out their profits. Moreover, the swift and user-friendly technological applications are attracting customers at a lower cost, casting doubt on the entrenched position of traditional commercial banks as well as the dynamics between financial institutions and customers (Brandl & Hornuf, 2020; Dorfleitner et al., 2017; Temelkov, 2018; Mallat, 2007). Other potential challenges from financial technology including cybersecurity issues, regulatory concerns, power outages, and the regulatory environment are also crucial factors. Existing research has not arrived at a consensus regarding the existence of a substitution effect or industrial synergy between financial technology firms and traditional financial institutions. Given this context and the absence of globally standardized measures for assessing the productivity and the growth of financial technology, the current study firstly directs the attention to the interaction between the bank performance, and non-financial digital payment platforms[1] that are identified as a burgeoning segment within the realm of financial technology (Dorfleitner et al., 2017; Chiu & Koeppl, 2019; Brandl & Hornuf, 2020; Dong et al., 2020; Sheng, 2021).

Due to data limitations, the first research question concerning the impact of digital payment platforms is conducted in the Chinese market. Employing both static (fixed effects model) and dynamic panel data models (Sys-GMM) while utilizing a dataset encompassing 1,747 observations that spans the period from 2011 to 2020, our estimated results reveal heterogeneous effects on the

[1] Chinese digital payment industry currently presents an obvious oligarchic competition. According to reports released by iResearch Consulting Group (Available online: https://www.iresearch.com.cn/report.shtml?classId=82), the Alipay and WeChat Pay platforms have the two largest market shares in the mobile digital payment field, accounting for over 50% and almost 40% in 2020, respectively.

profitability and risk-taking tendencies of various types of commercial banks. The findings indicate an adverse impact of digital payment platforms on the risk appetite among Chinese commercial banks, a trend that holds across different explanatory variables. Furthermore, digital payments are associated with a diminished profitability of urban and rural commercial banks, suggesting a developmental disadvantage for urban and rural commercial banks, though this result is not very robust. Additionally, the study observed that the implementation of various regulatory policies and the occurrence of COVID-19, transform the impact on profitability into a positive one. The inhibitory impact on risk-taking becomes more pronounced under these circumstances.

Against this background that the ever-increasing use of financial technologies, such as digital payment platforms, is posing a challenge to the profitability of the traditional financial industry and influencing risk management, incumbent commercial banks are reacting as an array of corporations such as acquisition, alliance, incubation, and joint venture (Austin & Dunham, 2022; Carlini et al., 2022; Drasch et al., 2018; Hornuf et al., 2021).Prior research has explored the impact of technology-driven M&As on firm performance (Akhtar & Nosheen, 2022; Austin & Dunham, 2022; Cloodt et al., 2006; McCarthy & Aalbers, 2016) and the market response to these technology-driven investments (Cappa et al., 2022; Carlini et al., 2022; Dranev et al., 2019; Hornuf et al., 2021). Despite the extensive body of research, a noticeable gap exists in comprehending how technology-driven M&As influence bank opacity, an inherent phenomenon within the banking industry (Akhigbe & Martin, 2006; Morgan, 2002) that hinders the assessment of asset value by external stakeholders and complicates the accurate evaluation of insiders' risk-taking behavior (Bushman, 2014; Flannery et al., 2004, 2013; Jones et al., 2012, 2013).

The utilization of technology improves overall performance and enhances accurate income prediction, which diminishes the motivation for income smoothing by recognizing loan loss provisions. Furthermore, the diversification of asset composition through technology-driven M&As and the diversification of investment opportunity through technological application reduce the information asymmetry between insiders and outsiders, ultimately lowering bank opacity. Conversely, the potential failure of technology-driven M&As intensifies the incentive for income smoothing through the recognition of loan loss provisions, thereby amplifying information asymmetry (Cappa et al., 2022; Dranev et al., 2019; McCarthy & Aalbers, 2016). The deepening opacity is further exacerbated by the accrual of goodwill resulting from M&As. The excess of fair value in a business acquisition is separately recorded as goodwill, and it is linked to factors such as customer loyalty, off-balance-sheet activities, and other relevant considerations. Determining the actual value of these factors can be challenging, adding complexity to the calculation of goodwill (Kwon & Wang, 2023; Xie et al., 2020). Consequently, our research secondly investigates whether technology-driven M&As contribute to an increase or decrease in bank opacity.

The second research question regarding the impact of technology-driven M&As is examined in a Japanese context. Specifically, we examine Japanese acquirers categorized as either listed banks, or the non-listed banks but belong to listed banking parent companies such as financial groups (hereafter Japanese-listed banks). We focus on 461 transactions over a period from April 1999 to March 2022, and utilize both propensity score matching (PSM) and differences-in-differences PSM (DID-PSM) in the Rubin Causal Model. Our findings present compelling evidence that technology-driven M&A transactions are negatively associated with bank opacity, a trend that is particularly pronounced for foreign technology-driven M&As.

Building upon our analysis, we conduct tests to assess the impact of technology-driven M&As on stock price synchronicity and risk composition, because bank opacity is a crucial factor that impacts stock price informativeness and synchronicity (Roll, 1988; Morck et al., 2000; Durnev et al., 2003; Jin & Myers, 2006; Dasguapta et al., 2010; and others). Previous studies suggest that low stock synchronicity may result from informed arbitrageurs integrating private information or occasional market noise (Roll, 1988; Morck et al., 2000; Durnev et al., 2003). Opaque stocks are also prone to experience sharp declines, leading to substantial negative returns (Jin & Myers, 2006). However, subsequent research presents contradictory viewpoints. In more transparent environments, less opaque stock prices are expected to offer greater insight into future events and higher synchronicity (Dasguapta et al., 2010). Along with our second research question, we further explore the relationship between stock price synchronicity and technology-driven M&As, especially when bank opacity is reduced through technology-driven M&A activities. Another consequence of the change in opacity is the alteration of risk composition, as increased transparency enhances the reliability of firm-specific information and refines the idiosyncratic component of risk. We also conduct a detailed analysis of the shift in stock risk composition resulting from technology-driven M&As.

The bank-quarter stock price synchronicity, betas, and idiosyncratic risk are calculated by the market model with daily equity returns and the TOPIX index from January 4, 1999, to June 30, 2022. Estimated results indicate that a bank's involvement in technology-driven M&As leads to decreased stock price synchronicity and betas, with no significant change observed for idiosyncratic risk. This finding holds consistently when employing different econometric techniques, using alternative market indices such as Nikkei 225, and considering alternative treatment variables. Opacity in financial markets can erode information efficiency, resulting in increased price synchronicity and a greater susceptibility to systemic market failure (Jones et al., 2012). Consequently, we also conclude that technology-driven M&As have the potential to diminish susceptibility to systemic market failure and enhance stock market stability.

On the balance sheet, these acquired software and technological products are documented as intangible assets, representing an opaque asset that simultaneously serves as an avenue for embracing digital transformations.

Intangible assets have long been acknowledged as increasingly pivotal for corporate development and firm value (Lev, 2003; Lim et al., 2020). Despite this recognition, there is a dearth of literature assessing the impact of intangible assets in the banking industry, primarily due to their opacity and limited information available from financial reports. Thus, this study also investigates how a bank's identifiable intangible assets (referred to as intangibles), predominantly comprised of software after excluding goodwill, impact the bank performance to emphasize the significance of detailed information disclosure.

Technology-orientated intangibles improve the bank's internal management efficiency and makes the information communication between departments more efficient (IMF, 2017). As banks possess more intangibles, they can offer a wider range of financial products and services, leading to the economics of scale while enhancing their market power and competitiveness. Thus, technology-oriented intangibles, functioning as intellectual capital, are anticipated to both enhance firm efficiency and establish a competitive advantage (Ordóñez de Pablos, 2003). By the quiet-life hypothesis (Berger & Hannan, 1998), banks' efficiency decreases as market power increases because larger banks are managed without cost minimization. However, the ES hypothesis (Berger, 1995) argues that efficiency improves banking profitability and increases concentration. Motivated by these perspectives, this study thirdly delves into the impact of intangibles on the bank's efficiency with addressing the issue of reverse causality between efficiency and competitiveness. Additionally, the study offers a plausible explanation for their relationship and underscores the significance of detailed accounting method for intangibles.

The third question exploring the impact of intangibles is investigated across various countries. We started by employing a stochastic meta-frontier analysis (Meta-SFA) to measure bank's efficiency (Battese et al., 2004; Huang et al., 2014; Lee et al., 2021). Individual efficiency scores are determined by regressing total costs against inputs and outputs within a single-country setup. Meta-efficiency scores are then estimated by regressing cost frontiers against inputs and outputs across multiple countries, capturing the multinational efficiency gap. Subsequently, the estimated efficiency scores (both individual efficiency and meta-efficiency) are regressed on intangibles using a two-way fixed effects model. Our dataset encompasses information from 624 commercial banks across four regions, comprising 30 countries: the European Union (EU, 27 countries), the United States (US), Japan (JP), and Mainland China (CN). This dataset provides a total of 5,277 observations over a 10-year period, spanning from 2012 to 2021. To address the reverse causality between efficiency and competitiveness, instrumental variables are incorporated into the estimation using a two-stage least squares (2SLS) approach and the generalized method of moments (GMM). The comprehensive findings from our estimation reveal that intangibles contribute to an increase in a bank's efficiency, with the fostering effects being particularly impactful on the meta-efficiency. While intangibles also exhibit a positive correlation with individual efficiency, the evidence is not entirely robust. Our interpretation of this result suggests an amelioration of macro-environmental restrictions. Nevertheless, the focus on intangibles may reduce a bank's core business activities, leading to decreased outputs and a relatively inconspicuous change in individual efficiency.

The removal of national restrictions on bank efficiency should contribute to perfect competition and then accelerate efficiency convergence. We further test the impact of intangible assets on efficiency convergence by the interaction term of intangibles and lagged efficiency scores, which indicates that intangibles positively predict efficiency convergence. Furthermore, the interaction term involving the Global Fintech Index highlights that the level of national fintech development influences the dynamics of competition and cooperation, creating distinctions among incumbent banks and potentially reducing meta-efficiency convergence. However, the response of banks, such as the procurement of technology-related products, tends to homogenize this differentiation, fostering convergence and enhancing the perfect competition of markets.

Collectively, our study delves into the impact of technological advancements on the banking sector, focusing notably on digital payment platforms, M&As, and intangible assets. We find that the profitability and risk-taking behaviors of incumbent banks are influenced by technology, leading them to actively engage in technology-related investments. This, in turn, reduces bank opacity and enhances stock market informativeness and stability. Nevertheless, we recognize the necessary for a more comprehensive disclosure of intangible assets in financial statements, given their substantial impact on bank performance, including bank efficiency and efficiency convergence.

Our study makes contributions to existing research in several ways. First, it extends the current understanding of the relationship between financial technology and established commercial banks, by particularly providing valuable insights into the development of rural commercial banks and those situated in developing areas. We also underscore the pivotal role of regulatory changes in shaping this dynamic landscape. Notably, previous research has overlooked the impact of digital payment on rural commercial banks, despite its numerous benefits for individuals in these areas. By integrating data from rural commercial banks, our study illuminates the challenges they face in harnessing fintech benefits. Some studies also lack post-2018 data, a period marked by the pandemic and the amplified advantages of contactless payment methods. Utilizing time dummy variables, we uncover the dynamic interplay between digital payment platforms, highlighting the need for regulatory intervention for rural commercial banks.

Second, our study contributes to the examination of technology engagement and financial stability. The goodwill in M&A activities are identified as a factor increasing bank opacity. Existing studies also highlight concerns about the convergence of the financial industry with other sectors, introducing external factors and posing risks to financial system stability. Our research provides additional evidence supporting the positive relationship between bank transparency and technology-driven M&As. Moreover, technology-driven M&As may benefit incumbent banks through knowledge synergy, reducing bank opacity and contributing to stock market stability. These findings offer policymakers insights into whether to permit financial institutions to engage in M&A activities in non-financial sectors.

Last, our analysis expands existing literature on bank efficiency and intangible assets. While previous research primarily focuses on the valuation of opaque assets, especially unrecorded intangibles, our study reveals that technology-related intangibles, despite being recognized as opaque assets, have the potential to enhance bank efficiency and efficiency convergence. This emphasizes the need for comprehensive disclosure of recorded intangible assets by both large and small banks, to strengthen external monitoring and aiding investors in accurate evaluation.

The present study is structured into 5 chapters. Chapters 2 to 5 comprehensively present our three research inquiries, encompassing literature reviews, methodologies, empirical results, and additional analysis for each chapter. Chapter 2 investigates the impact of digital payment platforms on bank profitability and risk-taking behavior within the Chinese market. Chapter 3 examines the effects of technology-driven M&As on bank opacity, stock price synchronicity, and risk composition in a Japanese context. Chapter 4 explores the impact of intangibles on efficiency and efficiency convergence across various countries. Last, we conclude and offer further discussion in Chapter 5.

2 The Impact of Digital Payment Platforms on Bank Profitability and Risk-Taking: Empirical Evidence from China

2.1 Introduction

Previous research hasn't reached a consensus on whether there is a substitution effect or a complementarity effect between financial technology firms and traditional financial institutions. Against this background, and in a vein where there are no globally common standards and academic consensus to measure the productivity and the growth of financial technologies, the present study focuses on the relationship between the performance of traditional banks and non-financial digital payment platforms, for the latter has been classified as a booming segment of financial technology (Dorfleitner et al., 2017; Chiu & Koeppl, 2019; Brandl & Hornuf, 2020; Dong et al., 2020; Sheng, 2021).

Our research question in this chapter is conducted in a Chinese context, of which non-financial digital payment platforms are also named third-party payment, such as Alipay and WeChat Pay (Temelkov, 2018). In China, third-party payment is a transaction service provided by third-party non-financial entities. In the scholarly literature, this kind of payment method is also termed mobile payment (Mallat, 2007), digital wallet (Thakor, 2020), and alternative payment (Dorfleitner et al., 2017). Hereafter, the terms digital payment and digital payment platforms are adopted in the present study. As they have developed, digital payment platforms have become an indispensable sector of people's daily lives, with a series of innovative and convenient functions. For example, digital payment brings together payment for online shopping, peer-to-peer money transfer

(Dorfleitner et al., 2017; Thakor, 2020), financing, wealth management, and even personal identity verifications[2], which is challenging traditional financial services and performance that exist today (Thakor, 2020), through impacting commercial banks' profitability (both interest and non-interest income) and risk-taking behaviors. Thus, the extent to which this new product impacts traditional financial institutions and what this development portends for the future of banking and payment systems may be excellent research questions.

Inspired by these reasons, employing both static (fixed effects model) and dynamic panel data models (Sys-GMM), using a dataset obtained from multiple sources which consist of 1,747 observations during a period from 2011 to 2020, this study investigates the impact of digital payment platforms on the profitability and risk-taking behaviors of Chinese commercial banks. Estimated results reveal heterogeneous impacts on the profitability and risk-taking of different types of commercial banks. Digital payments have been found to contribute to a reduced appetite for risk among urban and rural commercial banks, and this outcome remains robust across various explanatory variables. Furthermore, digital payment platforms could have a notably adverse impact on the profitability of urban and rural commercial banks, suggesting a developing disadvantage for urban and rural commercial banks, though this result is not very robust. Additionally, the study observed that the issuance and implementation of various regulatory policies by the country, coupled with the effects of COVID-19, transformed the impact on profitability into a positive one. The inhibitory impact on risk-taking became more notable under these circumstances. Finally, the study aims to shed light on how bankers facilitate the seamless integration of this innovation into the economy. The implications of our study are that banks could develop a close collaboration with financial technology firms, and rural commercial

[2] There are more services available on digital payment platforms like selecting and top-up social media memberships, calling a taxi, and checking medical insurance (Chen et al., 2021).

banks may need more regulatory support.

Our study contributes to prior research in several ways. First, it enhances the existing study on the relationship between financial technology and incumbent commercial banks. Previous studies have presented conflicting opinions regarding the impact of digital payment platforms on profitability and risk-taking in the banking sector. Our research offers empirical evidence supporting a negative relationship between digital payment platforms and both bank profitability and risk-taking behaviors. It is crucial to note that the Chinese banking sector differs from those of other countries, which is the largest bank-dominated financial system in the world (Wang et al., 2018). Consequently, understanding how the rapid development of technologies influences the Chinese banking system in the short term is vital for the global financial system. Additionally, within the unique context of oligarchic competition among digital payment platforms in China, small banks in this sector strive for survival by engaging in B2B settlements, which expedites the adoption of digital payment methods. The exaggeration of the benefits of contactless payment methods during the COVID-19 pandemic further emphasizes the potential continuous and widespread use of digital payment platforms even after the pandemic subsides, thereby impacting the global financial service system in the long run. Given the expanding usage of digital payment in the future, addressing these questions holds great significance for the Chinese government. It may prompt the government to implement measures regulating the financial services market accordingly.

Second, our study carries substantial value for countries aspiring to elevate their financial services through technological innovations. Unlike developed nations, China did not initially demonstrate a higher level of financial inclusion. Researchers have pinpointed that the significant expansion of financial inclusion in China can be attributed to the widespread adoption of network and mobile communication technologies (Guo et al., 2020). Consequently, delving into the impacts of these technologies on traditional financial institutions becomes a matter of great interest for countries striving to enhance their financial services through technological advancements.

Last, our research makes a meaningful contribution to the development of rural commercial banks and banks situated in developing areas, underscoring the crucial role of regulatory intervention. A notable gap in prior research lies in the omission of rural commercial banks from their analyses, despite the numerous benefits digital payment offers to individuals residing in rural areas. Some studies also lack data beyond 2018, a period that witnessed the pandemic and the exaggerated benefits of contactless payment methods. Moreover, regulatory changes can significantly impact the dynamics between digital payment platforms and traditional commercial banks. By incorporating data from rural commercial banks, our study sheds light on the challenges these banks face in leveraging fintech advantages. Using time dummy variables, we uncover the dynamic relationship between digital payment platforms. These findings underscore the necessity for intervention and support from regulatory authorities, particularly for rural commercial banks grappling with these challenges.

This chapter is organized into 5 sections. Section 2.2 introduces literature review related to the banking industry and financial technology, which is followed by hypothesis development. Then we describe the methodology that consists of empirical models, variables, and data in Section 2.3. Empirical results of baseline regression, an exploration of both heterogeneous and non-linear relationship, and robustness tests are reported in Section 2.4. Finally, we conclude and provide a further discussion in Section 2.5.

2.2 Literature review

In this section, we review existing studies about both the bank profitability and risk-taking behavior, and studies on the impact of digital payment platforms.

2.2.1 Bank profitability

Using samples within a single-country setup or a group of countries, previous research classified how bank-specific factors such as credit risk, capital ratio, interest-income ratio, and operating cost, industry-specific factors such as concentration measured by the Herfindahl-Hirschman Index, as well as macroeconomic factors such as GDP growth rate, impact the profitability of commercial banks. Some research examined these questions by employing a fixed effects model (Micco et al., 2007), while considering the persistence of profit, prior research also employed the techniques for dynamic panel estimation that deal with the biasedness and inconsistency of the estimates through a generalized method of moments (Athanasoglou et al., 2008; Dietrich & Wanzenried, 2011, 2014). Comparatively, taking different backgrounds and different measures for profitability such as return on (average) assets, return on (average) equity, net interest margin, and economic value-added, previous research showed that the impacts of determinants vary quite widely.

Capital ratio (*Capital*): Research (Dietrich & Wanzenried, 2011, 2014; García-Herrero et al., 2009) believes a higher capital ratio positively contributes to bank profitability for two key reasons. First, it signifies better creditworthiness. Second, a lower level of funding cost is associated with a higher capital ratio, as it represents the availability of proprietary funds to support a bank's business, acting as a safety net (Athanasoglou et al., 2008). In addition, basing the symmetric information assumption, banks expecting to have better performance credibly transmit their information through a higher capital ratio (Athanasoglou et al., 2008). Using panel data from 1985 to 2001, Athanasoglou et al. (2008) showed that bank capital measured by equity ratio positively predicted the ROA of Greek banks. While when Dietrich and Wanzenried (2011) examined other factors like interest income share and funding costs, they demonstrated that bank capital negatively predicts banking profitability in Switzerland.

Total assets ($Size$): Previous studies (Athanasoglou et al., 2008; Dietrich & Wanzenried, 2011, 2014; Pasiouras & Kosmidou, 2007) also have divergent opinions on whether larger banks have better profitability. The larger bank could benefit from economies of scale (higher operational efficiency) and economies of scope (higher degree of product and loan diversification). However, bank profitability may be damaged due to scale of inefficiencies such as bureaucratic (Berger et al., 1987). There is also plenty of empirical evidence. Considering different levels of the country's income, Dietrich and Wanzenried's other study (2014) adopted a comprehensive bank-level dataset and demonstrated bank size is negative on banking profitability in high-income countries but has no impact in low- and middle-income countries. These results are supplementary to their early research (2011) which found that bank size was positively related to the profitability of small banks before 2007 but negatively related to the profitability of large banks for the period after 2007.

Deposit growth ratio ($Deposit\ growth$): Previous research has inconclusive results on whether deposit growth has a positive impact on profitability. Dietrich and Wanzenried (2014) showed evidence that yearly growth of deposits is significantly positive related to profitability because banks can convert great growth of deposits into earning asset, expand their business, which will leading to better profitability. However, different view negated these results because the contribution of deposits growth ups to banks' ability to convert liability to earning assets (operating efficiency) and the credit quality of those earning assets.

Competition (HHI) *and efficiency* ($Efficiency$): Another string of research focused on the influence of industrial structure and documented how competition impacts profitability in the banking industry. In the traditional structure-conduct-performance (SCP) paradigm (Hannan, 1991), a lower level of competition (a higher level of concentration) benefits profitability because firms tend to collude with each other to obtain higher profits (Maudos & Fernández de Guevara, 2004). However, some research (Dietrich & Wanzenried, 2014) also demonstrated that concentration indexed by HHI is negatively related to banking profitability in middle- and high-income countries. One divergent view, the efficient-structure hypothesis (ES), argues that the positive relationship between concentration and profitability may be an incidental result because efficiency leads to an improvement in banking profitability and an increased concentration (Berger,1995).

2.2.2 Bank risk-taking

There is plenty of research on risk-taking (and fragility) in the banking industry, marked with Z-scores, non-performing loans, and loan loss provisions.

Competition (HHI): In line with the inconclusive arguments over profitability, extant literature has not reached a consensus on whether competition will worsen banking stability or not. Competition-fragility theory emphasizes that a lower level of competition enhances stability in the banking industry because bank enjoys more charter and franchise value, which results in greater opportunity costs during bankruptcy (Marcus, 1984; Keeley,1990; Hellmann et al., 2000), and concentrated banking systems create "capital buffers" against macroeconomic shocks (Hellmann et al., 2000; Boyd et al., 2004). In addition, Allen and Gale (2004) stated that as a price-taker in a competitive industry, banking has a decreasing incentive to support an insolvent bank, which intensifies the fragility. Thus, a concentrated banking system is more stable because there is less of a monitoring burden for banks. Empirical evidence can be inferred from Albaity et al. (2019) who analyzed a dataset from 18 MENA countries and demonstrated that both the Boone indicator and Lerner index have a negative relationship with Z-score (insolvency risk), while a positive relationship with non-performing loan ratio (credit risk).

Compared to traditional competition-fragility, the competition-stability theory argues that banks with high market power would take on the excessive risk because they are regarded as important institutions and receive subsidies from the government (too-big-to-fail) (Acharya et al., 2012; Boyd & De Nicolo, 2005; Kane, 2010; Mishkin, 1999). Meanwhile, banks with power may have a higher loan default probability because higher loan rates encourage borrowers to engage in more risky investment activities (Boyd & De Nicolo, 2005; Caminal & Matutes, 2002). Other research (Beck et al., 2006) emphasize the difficulty in monitoring a large and complex bank brings about inefficiency and fragility in the banking sector. This view is supported by empirical evidence which comes from Asia Pacific countries (Fu et al., 2014) and CIS countries (Clark et al, 2018), for they showed that the Lerner index negatively predicts Z-score. Recently, competition-fragility theory and competition-stability theory are reconciled because they could coexist and generates a non-linear relationship between competition and stability (Beck et al., 2013; Martinez Miera & Repullo, 2020).

Total assets (*Size*): The nexus of competition and fragility also guides how bank size and capital influence banking risk-taking. However, the conclusions are mixed. Research found that banks' fragility (Laeven & Levine, 2009) and banking systemic risk (Laeven et al., 2016) increase in bank size because of agency problems and moral hazard behaviors. In contrast, there is an analysis clarifying that bank size enhances bank stability and non-performing loans.

Capital ratio (*Capital*): Capital has been deemed a buffer to reduce insolvency risk (Repullo, 2004; Von Thadden, 2004) by improving risk management (Allen et al., 2011; Coval & Thakor, 2005). Using a dataset from 61 countries, Anginer et al. (2018) empirically showed that capital reduces banks' systemic risk. Berger and Bouwman (2013) provided evidence for this view and conclude that capital reduces bankruptcy during crises.

2.2.3 Impacts of digital payment platforms

In what follows in this section, we begin with a brief introduction of the current stylized facts of digital payment platforms in China and review previous research, which will help to set the guidelines for our hypothesis.

First, the total transaction growth rate facilitated by digital payment platforms from 2011 to 2020 significantly surpasses that of banking cards[3]. Consequently, the slower growth in card payment poses a challenge to the non-interest income (fee and commission income) of banks. Simultaneously, the wealth management function of digital payment platforms challenges the interest income of banks[4]. This disparity in returns adds to the challenges faced by banks in sustaining their interest income. Commercial banks may need to adjust their risk-taking tolerance for grinding out their profits and raise capital utilizing similar financial products with higher capital cost[5]. As a result, these fast and user-friendly transactions trigger a substitution effect and attract customers at a lower cost, which questions the dominant position of traditional commercial banks and the relationship between financial institutions and customers (Brandl & Hornuf, 2020; Dorfleitner et al, 2017; Temelkov, 2018; Mallat, 2007).

Using data collected from the Indonesia market, Phan et al. (2020) showed

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[3] Digital payment platforms reached CNY 271 trillion in 2020, marking a remarkable 116-fold increase from the CNY 2.3 trillion recorded in 2011. In contrast, banking cards issued totaled CNY 888 trillion in 2020, 3 times the value of digital payment platforms. However, this figure represents only a 2.7-fold increase compared to the 2011 value (Graph 2.1).

[4] Digital payment platforms yield significantly higher returns, with the Yu'e Bao monetary fund at the Alipay platform demonstrating a yield ranging from 1.5% to 7%, whereas traditional banks typically offer around 0.30%.

[5] Such as Zhaozhaoying monetary fund of China Merchants Bank.

that the growth of financial technology firms negatively predicts bank performance denoted by the ratio of net interest income to total assets, the ratio of net income to total assets, and the ratio of net income to total equities. Reasons may be that compared to traditional banks which are characterized by costly, old-fashioned, and cumbersome services (Brandl & Hornuf, 2017; Phan et al., 2020), financial technology triggered a substitution effect with its lower-cost, rapid, customer-oriented innovation (Chen et al., 2021; Brandl & Hornuf, 2020; Phan et al., 2020). Using the Peking University Digital Financial Inclusion Index of China (hereafter PKU-DFIIC), Zhao et al. (2022) examined the impacts of technological innovation on different banks (state-owned, joint-stock, urban commercial banks, and policy banks). In the robustness test of their analysis, they concluded that bank profitability and capital quality decrease in technological innovations in the aggregate. Xia and Chunsom (2018), using data gathered from digital payment reports from iResearch Consulting Group[6] as well as data of 16 listed commercial banks, concluded that payment via mobile phone reduces non-interest income. They also investigated the different impacts on small-medium commercial banks and large state-owned commercial banks. Results showed that the non-interest income of large state-owned commercial banks, compared to that of small-medium commercial banks, is more negatively influenced by digital payment.

On the contrary, an alternative perspective suggests that commercial banks can still benefit from a complementarity effect through collaboration with non-financial digital payment platforms and giant tech firms[7][8]. Financial technology

[6] A Chinese company engaged in market research.

[7] In May 2016, China Everbright Bank (CEB) formed a formal cooperation with Alipay in which users can use a credit score that is calculated according to their consumption at the Alipay platform as the reference for applying for a credit card.

[8] There is strategic cooperation between big banks and big tech firms, especially the cooperation between Bank of China and Tencent, Industrial and Commercial

may be positively correlated with bank profitability by reducing operating costs and improving comprehensive competitiveness (Dong et al., 2020; Wang et al., 2021). Digitization also generates a large amount of data for the banking industry to conduct analysis, which reduces the cost of obtaining information, increases the transparency of the market, and ameliorates information asymmetries (Chen et al., 2021; Yao & Song, 2021).

Empirical evidence also comes from the analysis of the Chinese market that are conducted by Cheng and Qu (2020), Dong et al. (2020), Wang et al. (2021), and Yao and Song (2021). By constructing a bank financial technology index, Cheng and Qu (2020) showed that great improvement of financial technology in China negatively predicts credit risk in Chinese banking sector during a period from 2008 to 2017. Hu et al. (2022), using PKU-DFIIC and data of Chinese commercial banks from 2011 to 2020, concluded that fintech reduces the risk-taking of Chinese commercial banks. Their results are more significant for giant banks.

Scholars (Thakor, 2020) also concluded that the answer to the impact of financial innovations on banks depends on what kind of economy we are talking about, for one of the reasons is there is a lower percentage of the population in developing countries uses the banking system than in developed countries. Guo and Shen (2016) and Uddin et al. (2020) proved there is a convex relationship between financial technologies and bank risk-taking, for financial technology both reduces the cost of risk management and raises the capital cost, which exacerbates banks' risk-taking.

Taken together, previous research has controversial opinions about the impact on profitability and risk-taking from digital payment platforms. What's more, most research did not take rural commercial banks into their analysis, even though

Bank and JingDong, Agriculture Bank of China and Baidu, China Construction Bank and Alibaba.

digital payment provides many benefits for people living in rural areas. Some examinations did not include data after 2018, the period of the pandemic when the benefits of contactless payment methods are exaggerated. Additionally, changes in regulations may impact the dynamics between digital payment platforms and traditional commercial banks. The Chinese government promulgated regulations in 2013 that clients' reserves received by non-financial payment institution must be deposited in the special-purpose deposit account at banks[9], which may benefit banks through collecting scattered funds in the market and raising capital. Another regulation was announced in 2016 that all online transactions involving bank accounts must be processed at the NetsUnion platform, an online settlement platform for non-financial institutions[10]. This has disadvantaged digital payment platforms in terms of negotiating with individual banks.

Against the inconclusive arguments and limitations of previous research, we employ time dummy variables to manage the impact of regulatory changes and incorporate previously discussed factors from relevant studies. The present study hypothesizes that there may be both a competitive and cooperative relationship between digital payment platforms and commercial banks.

H2.1a: *Digital payment platforms negatively predict commercial bank profitability.*

H2.1b: *Digital payment platforms positively predict commercial banks profitability.*

H2.2a: *Digital payment platforms positively predict commercial bank risk-*

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[9] Available online: http://www.pbc.gov.cn/en/3688253/3689009/3788477/3901098/index.html.

[10] Inquiries related to NetsUnion can be referred to the homepage of company or reports from a consulting company. For example, information related to NetsUnion is available at: https://www.nucc.com/about.html

taking.

H2.2b: *Digital payment platforms negatively predict commercial bank risk-taking.*

2.3 Methodology

2.3.1 Panel data analysis

In the banking literature, it is customary to employ a fixed effects model for panel data conditioning on unobservable effects (Athanasoglou et al., 2008; Micco et al., 2007; Uddin et al., 2020; and others). Thus, the baseline regression is estimated with two-way fixed effects model (formula 2.1).

Fixed effects model

$$Dependent_{it} = \beta_1 PKU - DFIIC_{it} * Bank\ nature_i + \sum_k \beta_k Controls_{kit} + \mu_i + \lambda_t + \epsilon_{it} \quad (2.1)$$

Our banking panel data contains both a cross-sectional dimension and a time-series dimension, with i identifying banks and t identifying time. μ_i denotes unobservable individual-specific effects. λ_t denotes the time-specific effect of each year. ϵ_{it} represents stochastic disturbance with independent and identically distributed $IID\,(0, \sigma^2)$. This model requires that ϵ_{it} is strictly exogenous ($E(\epsilon_{it} \mid \{X_{1is}, \ldots, X_{kis}\}_{s=1}^{T}) = 0$).

Following previous research (e.g., Albaity et al., 2019; Clark et al., 2018; Dietrich and Wanzenried, 2011, 2014), we employ return on assets (ROA) and return on equity (ROE) as the measures of profitability, while nonperforming loan ratio (NPLR) and loans provision ration (LPVR) as measures of risk-taking. Following Zhao et al. (2022) and Hu et al. (2022), the main explanatory variable in our analysis is a panel index, the Peking University Digital Financial Inclusion Index of China (PKU-DFIIC), developed by the Institute of Digital Finance at Peking University and Ant Financial Services Group (Guo et al., 2020). Different from previous research, we matched a country-level, province and prefecture-level, municipality-level index for Chinese commercial banks conditioning on the different geographic locations and clients of bank's cooperation and subsidiaries.

We also took a logarithmic treatment of these indexes for interpretability. The impacts due to different bank nature and promulgated regulations are also tested by controlling bank nature dummy variable as well as the period dummy variable. A vector of bank and country characteristics is controlled to reduce concerns that $Cov(X_{it}, \epsilon_{it}) \neq 0$ （X_{it} represents explanatory variables $PKU - DFIIC_{it}$） and to mitigate potential omitted-variable problems.

Then, we conduct a two-way random effects model accompanied by the Breusch-Pagan Lagrange multiplier test and the Hausman test for determining which estimation technique is required, which shows that the two-way fixed effects model is more efficient for the analysis of banking profitability and risk-taking. Presented results are estimated using robust standard deviation on the account of heteroskedasticity.

Based on the empirical results of the above analysis, we produce the most robust results by different independent variables (the logarithm of the total transactions by digital payment platforms) as well as different econometric techniques (dynamic panel data model). Here, we discuss the model employed for robustness tests first.

Sys-GMM model

$$\begin{aligned} Dependent_{it} = & \sum_k \rho_k Dependent_{i,t-k} + \beta_1 PKU - DFIIC_{it} * Bank\ nature_i \\ & + \sum_k \beta_k Controls_{kit} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{2.2}$$

Being consistent with previous research (e.g., Athanasoglou et al., 2008; Berger et al., 2000; Dietrich & Wanzenried et al., 2011, 2014; Dong et al., 2020; Fang et al., 2019), we additionally employed the system generalized method of moments (Sys-GMM, formula 2.2) to analyze dynamic panel data for bank performance may show a tendency to persist over time (Berger et al., 2000). The coefficient of lagged term, ranging from 0 and 1 indicates the persistence of dependent variables (profits and risk-taking behaviors), reflecting obstacles of market competition and informational opacity. But they are expected to gradually revert to their normal level. A value approaching 0 indicates a perfect competitive industry, whereas a value nearing 1 implies a less competitive structure. Hence, the application of Sys-GMM is crucial, given the consideration of the imperfect competition in the Chinese banking industry.

Compared to the static panel analysis model above, the dynamic panel analysis above is augmented with lagged items, $Dependent_{i,t-k}$ which is k-period lagged dependent variables, among the regressors. The correlation between independent variables and error term breaks strict exogeneity in the differenced equations and makes estimators lose their consistency. Following Arellano and Bond (1991), the lags of the dependent variable itself are valid instruments in the differenced equations, conditioning on the inexistence of autocorrelation between error terms (Diff-GMM). What's more, following Arellano and Bover (1995), as well as Blundell and Bond (1998), Sys-GMM can be employed to account for endogeneity. It uses the lagged value of dependent variables in both differences and levels as instrument variables, conditioning on the inexistence of autocorrelation between error terms and the inexistence of correlation between instruments and effects. We conducted the Arellano-Bond test on the second-order residual serial correlation coefficient and the Hansen test for over-identified restrictions.

2.3.2 Variables

When we use the above methods to analyze the impact of digital payment platforms on the profitability and risk-taking of commercial banks, return on assets (ROA in %) and return on equity (ROE in %) are chosen as the measures of profitability. ROA indicates the ability of a bank's management to generate revenues from the bank assets, and ROE indicates the ability to generate revenues from the bank equity. For the calculation of ROA and ROE, we use the average value of assets or equity for 2 consecutive years because profit is a flow variable generated during the year. Nonperforming loan ratio (NPLR in %) and loans provision ratio (LPVR in %) are chosen as measures of risk-taking. NPLR represents the ratio that loan borrowers have difficulty to continue making repayment towards the loan. In China, under the five-tier system promulgated by China Banking Regulatory Commission (CBRC), bank loans are classified according to their inherent risks into the performing, watch-list, substandard, doubtful, and loss categories. The last three categories are known as non-performing loans. LPVR represents how protected a bank is against total loans. Loan loss provision consists of general reserve (1% at least for various loans), specialized reserve (2% for watch-list, 25% for substandard, 50% for doubtful, 100% for loss category), and special reserve. A higher level of ROA and ROE indicate better bank profitability, while a higher level of NPLR and LPVR indicates a lower credit quality and higher risk-taking behavior.

Our explanatory variable is the logarithm of PKU-DFIIC in different levels consisting of country level, province and prefecture level, as well as municipality level. We matched large state-owned commercial banks (6 banks) and joint-stock commercial banks (12 banks) with the country-level index, urban commercial banks (96 banks) with the province and prefecture-level index, rural commercial banks (86 banks) with municipality-level index. In this study, the total transactions (in trillion Chinese yuan) by digital payment platforms are employed as an additional explanatory variable for the robustness test. We took a logarithmic treatment of these explanatory variables.

Following the analysis by previous research, we use liquid assets ratio ($Liquidity$), equity ratio ($Capital$), deposits growth rate ($Deposit\ growth$), operating efficiency ($Efficiency$), interest income ratio (IIR), fund cost ($Fund\ cost$), bank size ($Size$), the shareholding ratio of the largest shareholder ($Major\ shareholder$), and GDP growth rate ($GDP\ growth$) as control variables. The definition of variables we employed is shown as in Table A2.1 in Appendix 2.1.

2.3.3 Data and descriptive statistics

Our data is obtained from multiple sources. The annual accounting data of banks is collected from Wind, a leading-edge financial data services and analytical tools provider. Manually collected data from banks' annual reports is used to retrieve abnormal values and missing data. Data about province and prefecture-level GDP growth rate are gathered from the National Bureau of Statistics. The main measure for digital payment platforms, Peking University Digital Financial Inclusion Index of China (PKU-DFIIC), is supplied by the Institute of Digital Finance at Peking University. We also used total transactions of digital payment platforms from reports released by iResearch Consulting Group, a Chinese company engaged in market research.

Table 2.1 shows the descriptive statistics of the variables used in the analysis. Our data will focus on the 200 Chinese commercial banks over a period from 2011 to 2020. We restricted our sample to banks with at least 5 years of data, which provides a total sample of 1,747 observations. The average ROA is 1.29%, with a standard deviation of 0.58%. During the sample period of 2011 to 2020, there is a decline in ROA for all types of commercial banks (Graph 2.2). NPLR of all types of commercial banks was an increasing tendency from 2011 to 2015, with a mean of 1.62% and a volatility of 1.01%. The NPLR of urban commercial banks and rural commercial banks was higher than that of the other two types of commercial banks from 2016 to 2020 (Graph 2.3). Regarding our explanatory variable, Graph 2.4 shows rapid growth of the province and prefecture-level PKU-DFIIC. The logarithm of PKU-DFIIC is slightly higher in areas with lower GDP growth rates (such as coastal provinces) than in areas with higher GDP growth rates (such as southwestern provinces). The logarithmic treatment is taken for interpretability, and logs have a mean of 5.31 with a small standard deviation of 0.51 shown in Table 2.1. Graph 2.5 shows that the rapid growth of the utilization of digital payment platforms is mainly an account of the use of mobile digital payment platforms. We checked abnormal variables to ensure other variables are within a reasonable range and to provide a good sample basis for empirical analysis.

To identity the amount of multicollinearity among our regressors, the variance inflation factor (VIF_j) which equal to the ratio of the overall model variance in a multiple regression model to the variance of a model that includes only single independent variable j, is calculated and presented as in Table A2.2 in the Appendix 2.2. A higher VIF for a variable indicates a great degree of linear relationship to other regressors, which reduces the statistical significance of regressors. In the present study, a VIF above 5 indicates high multicollinearities. Presented VIF in Appendix 2.2 shows no existence of high multicollinearities.

2.4 Empirical results

2.4.1 Baseline regression

In this section, we begin to illustrate the estimated results of baseline regression in Table 2.2. Before discussing the impacts of digital payment platforms, we first summarize the results of control variables.

In column 1 of Table 2.2, the positive coefficient (0.038) of the $Capital$ confirms that the capital ratio is significantly positive with ROA, which may be because it indicates lower risks and funding costs (García-Herrero et al., 2009; and others). The presented results also showed that in the Chinese banking industry, the liquid asset ratio is significantly positive with ROA (0.023 in column 1) and ROE (0.287 in column 2), which is in line with previous research (Athanasoglou et al., 2008; Dietrich & Wanzenried, 2011, 2014). The lower operating efficiency of Chinese banking sector is significantly negative with ROA (-0.030 in column 1) and ROE (-0.393 in column 2) and being significantly positive with NPLR (0.038 in column 3) and LPVR (0.020 in column 4), confirming the efficient-structure hypothesis (Berger,1995). The result of our main explanatory variable (PKU-DFIIC) is that it positively predicts ROA (0.128 in column 1) aggregately but has no impact on other variables. We further our analysis by delving into the heterogeneous impacts to produce the most robust results, with bank nature and regulation change as dummy variables.

2.4.2 Heterogeneous and non-linear impacts

Table 2.3 shows the heterogeneous impacts of digital payment platforms on different types of commercial banks. The result of our main explanatory variable (PKU-DFIIC) is that it negatively predicts ROA for all types of commercial banks except of joint-stock commercial banks, while it also negatively predicts ROE for large state-owned commercial banks. Our results also show that rural commercial banks' ROA is reduced by digital payment platforms (PKU-DFIIC) more than other types of commercial banks. A one-unit change in PKU-DFIIC results in a -0.561 change in the expected value of the profitability of rural commercial banks represented by ROA when all the predictors are held constant. Reasons may be that digital payment platforms led to a lowered non-interest income by reducing banking transaction services and made an adverse contribution to interest income due to monetary funds and other investments opportunities. What's more, joint-stock commercial banks have more flexibility than large state-owned commercial banks that are burdened with certain social responsibilities (Dong et al., 2014), and joint-stock commercial banks also have more sources of interest than urban and rural commercial banks.

Columns 3 and 4 show that digital payment platforms have no significant impact on NPLR, but it reduces LPVR for all types of commercial banks, claiming that digital finance may decrease risk-taking behavior. It may be due to that banks' risk-taking behavior may decrease in the utilization of big data generated by platforms, the reduction of risk management costs, and the alleviation of information asymmetries (Vives, 2017; Zhao et al., 2022).

As mentioned in Section 2.2.3, due to comprehensively tightened regulation in 2013 and in 2016, we conducted a robustness test employing the period dummy variable 1 for 2011-2013, 2 for 2014-2016, 3 for 2017-2019, and 4 for 2020 in consideration of COVID-19. The results in Table 2.4 confirm that the impact on profitability (ROA) of digital payment platforms gradually waned and then turned to a positive effect. Further, the utilization of digital payment platforms reduces risk-taking (NPLR and LPVR) in the banking sector, and the effect became more notable as the country issued and implemented an array of measures or regulatory policies.

2.4.3 Robustness test

In 2.4.3, we present estimated results of the robustness test with different econometric techniques and different independent variable. To get more definite evidence, our research questions are also regressed with the dynamic panel model (Sys-GMM), conditioning that bank performance may show a tendency to persist over time (Berger et al., 2000). For the sake of brevity, we discuss the coefficients of interest after regression. The estimated results of Sys-GMM are reported in Table 2.5. For the persistence coefficient measures, all these equations present persistence of banks' profitability and risk-taking, confirming that profitability and risk-taking of the previous period will last from one year to the next. The Arellano-Bond test for AR (2) and Hansen test of over-identified restrictions failed to reject the null hypothesis at a significance level of 5%, indicating the inexistence of autocorrelation and overidentification.

The results in columns 3 and 4 of Table 2.5 all indicate the negative relationship between banks' risk-taking and digital payment platforms. The coefficients are negative at a significance of 1% for all types of commercial banks, implying that digital finance reduces the risk-taking behavior of the Chinese commercial banking sector.

The PKU-DFIIC discussed is a proxy measuring user coverage of internet financial services only based on underlying data of Ant Financial Services' transaction accounts. Hence, we then used and took logarithmic treatment for the total transactions of digital payment platforms (in trillion) for robustness checks. The results shown in Table 2.6 are estimated by the Sys-GMM. The utilization of digital payment platforms makes an adverse contribution to the profitability of urban commercial and rural commercial banks (ROAE). It also decreases the risk-taking behavior of Chinese commercial banks, which in line with previous results.

2.5 Conclusions and limitations

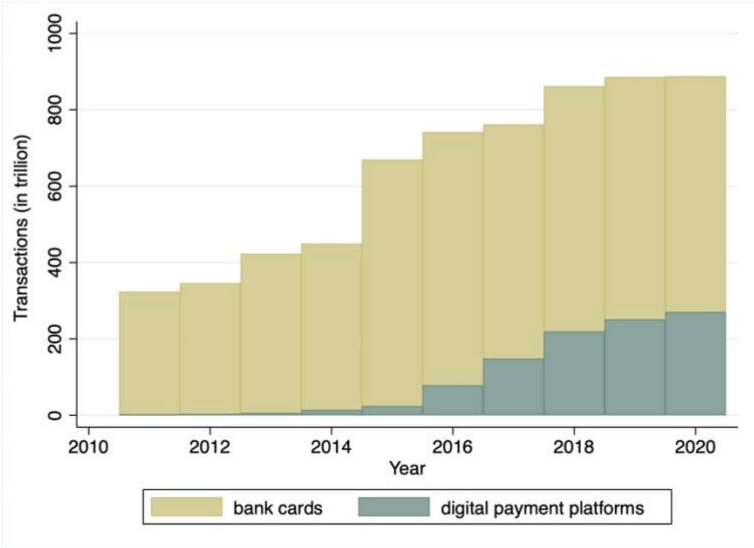
In a vein that technological innovations question traditional commercial banks' dominant position, for instance, the transaction system is challenged by non-financial digital payment platforms, the present study empirically investigated the extent to which digital payment platforms will impact the profitability and risk-taking in the Chinese banking sector. The results are heterogeneous and non-linear when augmented with bank nature and period dummy variables due to regulation changes and COVID-19. In sum, our results indicate that, digital payment led a lowered risk-taking for Chinese commercial banks, and this result remains robust across different explanatory variables. What's more, even though not very robust, the digital payment platforms could have an adverse impact on the profitability of urban and rural commercial banks, confirming a disadvantage of urban and rural commercial banks' development. We also found that as the country issued and implemented an array of measures or regulatory policies and due to COVID-19, the negative effect turned to a positive effect on profitability, and the inhibitory impact on risk-taking became more notable.

Putting our findings in a broader context, our study may have significant value for both countries where there is ascending development of financial technology, and countries where the development of financial technology is in an embryonic stage, but regulators may want to improve financial services and financial inclusion by the combination. The present study implies that in the future, the relationship between traditional financial institutions and emerging financial technologies, as well as the development of these industries, depends on whether banks and financial technology companies desire and approach cooperation (Brandl & Hornuf, 2020; Temelkov, 2018) and regulatory intervention changes. First, banks could develop a close collaboration with financial technology, which is already a trend in China. Through cooperation, banks will enjoy benefits like lower capital expenditure for risk management due to big data, increased access to customers in younger age groups and customers in distant geographic locations. Financial technology companies may enjoy the benefits of the brand reputation and large customer base of banks. Second, compared with some banks that have started a strategic collaboration with financial technology companies, rural commercial banks and banks located in developing areas may be at a disadvantage, which makes them need more support from the government. More important, rural commercial banks have a much higher non-performing loan ratio than other banks (Graph 2.3), which may be alleviated through cooperation with financial technology companies.

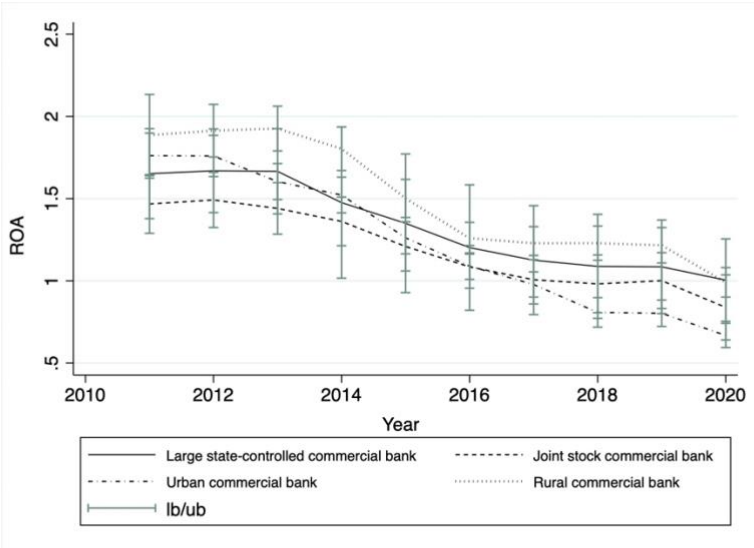
Finally, the present study still has several limitations. For example, through both the panel index ($PKU-DFIIC$) and series variable ($Digital$) we employed, there are still no common standards and sufficient data for measuring the development of digital payment platforms. What is more, the examining question is analyzed only in a Chinese context, which may not be practicable for other countries because of the existence of different industrial characteristics and cultures. Our further studies may focus on efficiency or their relationship from a perspective of the structural model while employing more sufficient and accurate data. Last, the risks of cooperation cannot be ignored. Cybersecurity issues, regulatory issues, and even power outages are potential challenges. The regulatory environment and converged infrastructures are also key factors.

Graphs and Tables

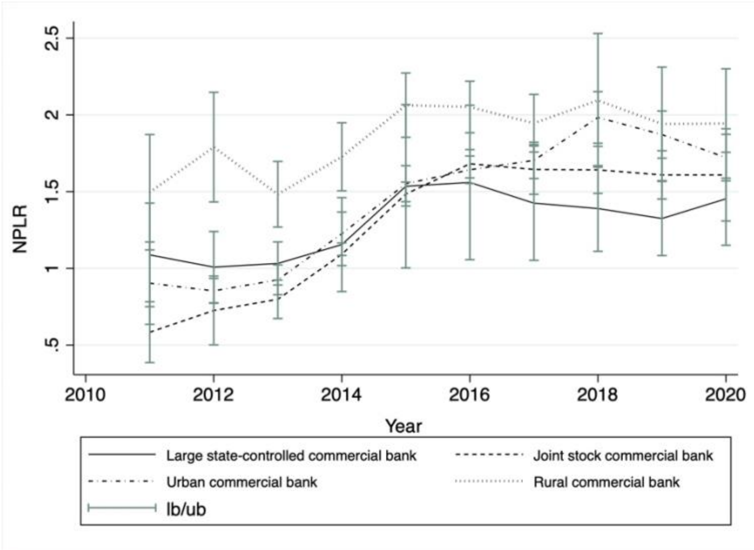
The graphs and tables discussed in the present study are displayed here.



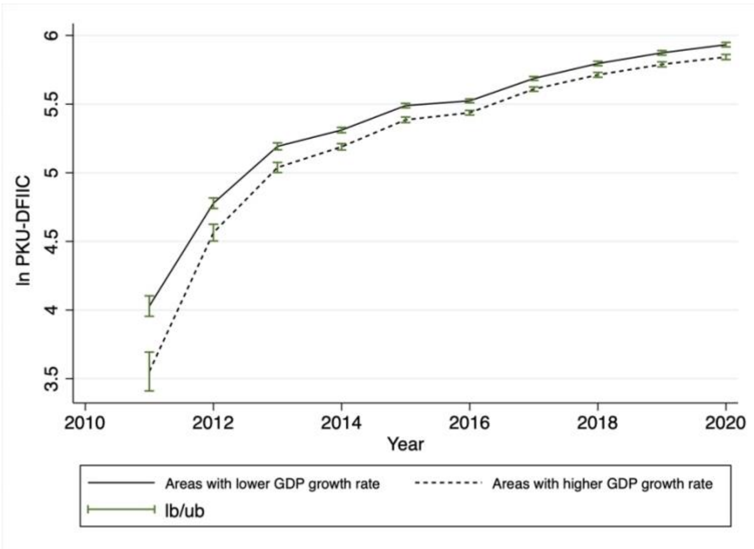
Graph 2.1 Transactions by bank cards and non-financial payment platforms



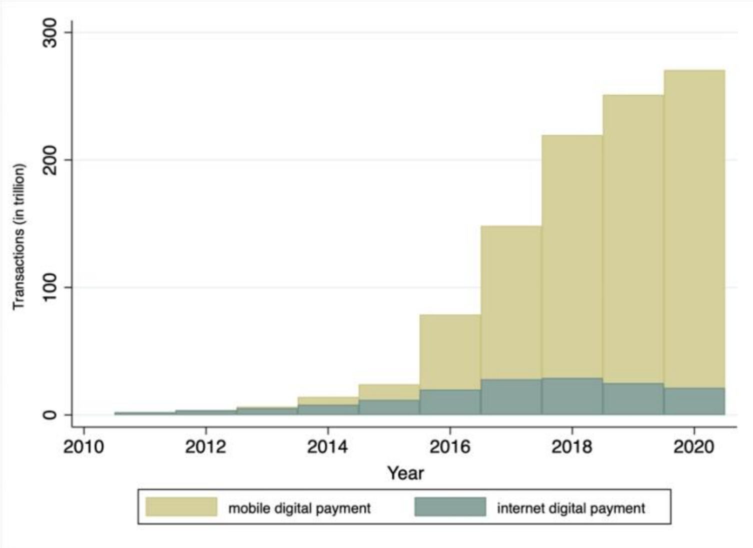
Graph 2.2 ROA of different types of commercial banks



Graph 2.3 NPLR of different types of commercial banks



Graph 2.4 Province and prefecture-level PKU-DFIIC of different areas



Graph 2.5 Transactions by digital payment platforms

Table 2.1 Descriptive statistics

Variable	Obs.	Mean	Std.Dev.	Min	Max
Panel A: Bank profitability and risk-taking					
ROA	1747	1.290	0.580	-0.080	4.128
ROE	1747	17.415	7.751	-1.190	65.272
NPLR	1747	1.624	1.012	0.010	12.250
LPVR	1581	3.697	1.267	1.050	10.040
Panel B: Digital payment					
PKU-DFIIC	1747	5.315	0.509	2.909	6.068
Digital	1747	3.810	1.641	0.833	5.601
Panel C: Control variables					
Liquidity	1747	13.044	4.449	4.930	42.432
Capital	1747	7.658	1.922	2.984	32.510
Deposit growth	1747	15.683	13.199	-86.757	249.155
Efficiency	1747	59.836	12.070	13.444	108.966
IIR	1747	78.350	18.401	-11.425	132.062
Fund cost	1747	3.309	1.233	1.323	12.305
Size	1747	25.511	1.655	21.937	31.088
Major shareholder	1747	16.376	13.657	0.417	83.080
GDP growth	1747	7.468	2.314	-5.000	15.400

Notes: There are four types of commercial banks: large state-owned commercial banks (6 banks), joint-stock commercial banks (12 banks), urban commercial banks (96 banks), and rural commercial banks (86 banks). 77 banks are located in 35 coastal municipalities, while 123 banks are located in 76 inland municipalities in China.

Table 2.2 Empirical results of baseline regression

	ROA	ROE	NPLR	LPVR
	Fixed effects	Fixed effects	Fixed effects	Fixed effects
PKU-DFIIC	**0.128*** **(0.074)**	**-1.040** **(1.378)**	**0.280** **(0.256)**	**-0.444** **(0.343)**
Capital	0.038*** (0.011)		0.011 (0.019)	0.023 (0.024)
Liquidity	0.023*** (0.006)	0.287*** (0.089)	-0.004 (0.011)	0.040*** (0.014)
Deposit growth	0.001 (0.001)	0.014 (0.012)	-0.008*** (0.003)	-0.003 (0.003)
Efficiency	-0.030*** (0.001)	-0.393*** (0.020)	0.038*** (0.004)	0.020*** (0.004)
IIR	-0.000 (0.001)	-0.010 (0.009)	-0.001 (0.001)	-0.004*** (0.002)
Fund cost	-0.011 (0.013)	0.014 (0.194)	-0.022 (0.027)	0.057** (0.048)
Size	-0.161** (0.072)	1.702 (1.086)	0.130 (0.194)	0.080 (0.242)
Major shareholder	-0.003 (0.003)	-0.048 (0.030)	-0.005 (0.006)	-0.008 (0.005)
GDP growth	0.002 (0.008)	-0.018 (0.117)	-0.019 (0.020)	-0.034 (0.022)
_cos	6.225*** (1.808)	5.524 (27.178)	-4.545 (4.487)	1.842 (5.981)
Bank-fixed	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes
N	1747	1747	1747	1581
R2	0.839	0.806	0.318	0.146

*Notes: The present study uses an analyzing power of 10%, which means the null hypothesis (H_0: Digital payment has no impact on the profitability or risk-taking of commercial banks) will be rejected if the t value in the critical region is 5% for each side. We performed the Hausman test (1978) to choose between the fixed effects model and random effects model, which indicated that the fixed effects model is more efficient than random effects in our analysis (F-test and Breusch-Pagan Lagrange multiplier test also indicated the efficiency of these two basic models when being compared to pooled OLS). We illustrate results estimated using robust standard deviation on the account of heteroskedasticity. The standard errors are reported in parentheses. *, **, *** are designated for the level of significance of 10%, 5% and 1%, respectively.*

Table 2.3 Heterogeneous impacts

	ROA	ROE	NPLR	LPVR
	Fixed effects	Fixed effects	Fixed effects	Fixed effects
1. Large state-owned commercial bank * PKU-DFIIC	**-0.234*** (0.091)**	**-3.258*** (1.750)**	**0.156 (0.276)**	**-1.403*** (0.422)**
2. Joint-stock commercial bank * PKU-DFIIC	**-0.093 (0.095)**	**-2.962 (1.945)**	**0.238 (0.276)**	**-1.241*** (0.448)**
3. Urban commercial bank * PKU-DFIIC	**-0.254*** (0.095)**	**-2.711 (1.779)**	**0.147 (0.280)**	**-1.429*** (0.457)**
4. Rural commercial bank * PKU-DFIIC	**-0.561*** (0.152)**	**-4.454 (2.833)**	**0.052 (0.502)**	**-2.110*** (0.697)**
Capital	0.032*** (0.010)		0.009 (0.018)	0.013 (0.024)
Liquidity	0.020*** (0.005)	0.275*** (0.083)	-0.006 (0.011)	0.036*** (0.014)
Deposit growth	0.001 (0.000)	0.015 (0.012)	-0.008** (0.003)	-0.003 (0.003)
Efficiency	-0.031*** (0.001)	-0.397*** (0.021)	0.038*** (0.004)	0.019*** (0.004)
IIR	-0.000 (0.001)	-0.010 (0.009)	-0.001 (0.001)	-0.004** (0.002)
Fund cost	-0.015 (0.013)	-0.016 (0.190)	-0.023 (0.027)	0.049 (0.049)
Size	-0.191*** (0.068)	1.348 (1.129)	0.124 (0.235)	-0.005 (0.247)
Major shareholder	-0.004 (0.002)	-0.048* (0.029)	-0.005 (0.006)	-0.009* (0.005)
GDP growth	-0.009 (0.008)	-0.046 (0.123)	-0.023 (0.020)	-0.051*** (0.022)
_cos	9.242*** (1.765)	24.806 (28.474)	-3.625 (6.203)	9.473 (6.170)
Bank-fixed	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes
N	1747	1747	1747	1581
R2	0.849	0.807	0.319	0.160

*Notes: The present study uses an analyzing power of 10%, which means the null hypothesis (H_0: Digital payment has no impact on the profitability or risk-taking of commercial banks) will be rejected if the t value in the critical region is 5% for each side. We performed the Hausman test (1978) to choose between fixed effects model and random effects model, which indicated that the fixed effects model is more efficient than random effects in our analysis (F-test and Breusch-Pagan Lagrange multiplier test also indicated the efficiency of these two basic models when being compared to pooled OLS). We illustrate results estimated using robust standard deviation on the account of heteroskedasticity. The standard errors are reported in parentheses. *, **, *** are designated for the level of significance of 10%, 5% and 1%, respectively.*

Table 2.4 Non-linear impacts

	ROA	ROE	NPLR	LPVR
	Fixed effects	Fixed effects	Fixed effects	Fixed effects
1. 2011-2013 * PKU-DFIIC	**-0.187** **(0.180)**	**-1.458** **(3.081)**	**-1.667***** **(0.580)**	**-2.551***** **(0.795)**
2. 2014-2016 * PKU-DFIIC	**0.302** **(0.261)**	**4.048** **(4.204)**	**-3.449***** **(1.265)**	**-3.323***** **(1.169)**
3. 2017-2019 * PKU-DFIIC	**0.651*** **(0.342)**	**5.318** **(5.540)**	**-5.414***** **(1.928)**	**-3.554**** **(1.370)**
4. 2020 * PKU-DFIIC	**0.738***** **(0.361)**	**6.211** **(5.659)**	**-6.041***** **(1.964)**	**-3.540***** **(1.627)**
1. Large state-owned commercial bank * PKU-DFIIC	0.145 (0.092)	-0.250 (1.588)	0.947*** (0.259)	0.916*** (0.388)
2. Joint-stock commercial bank * PKU-DFIIC	0.288*** (0.094)	0.064 (1.710)	1.020*** (0.251)	1.076*** (0.411)
3. Urban commercial bank * PKU-DFIIC	0.116 (0.096)	0.237 (1.641)	0.978*** (0.256)	0.907*** (0.382)
Capital	0.031*** (0.010)		0.014 (0.017)	0.013 (0.024)
Liquidity	0.018*** (0.005)	0.263*** (0.086)	0.003 (0.012)	0.038*** (0.014)
Deposit growth	0.001 (0.001)	0.014 (0.012)	-0.008*** (0.003)	-0.003 (0.003)
Efficiency	-0.031*** (0.001)	-0.397*** (0.021)	0.037*** (0.004)	0.019*** (0.004)
IIR	0.000 (0.001)	-0.010 (0.009)	-0.001 (0.001)	-0.004** (0.002)
Fund cost	-0.015 (0.013)	-0.017 (0.188)	-0.022 (0.026)	0.049 (0.049)
Size	-0.208*** (0.069)	1.230 (1.121)	0.203 (0.232)	0.010 (0.248)
Major shareholder	-0.004 (0.002)	-0.047 (0.029)	-0.007 (0.006)	-0.010* (0.005)
GDP growth	-0.013* (0.008)	-0.079 (0.123)	-0.007 (0.020)	-0.046** (0.022)
_cos	8.677*** (1.772)	19.848 (28.302)	-1.073 (5.591)	10.270* (6.137)
Bank-fixed	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes
N	1747	1747	1747	1581
R2	0.852	0.808	0.344	0.162

*Notes: The present study uses an analyzing power of 10%, which means the null hypothesis (H_0: Digital payment has no impact on the profitability or risk-taking of commercial banks) will be rejected if the t value in the critical region is 5% for each side. We performed the Hausman test (1978) to choose between fixed effects model and random effects model, which indicated that the fixed effects model is more efficient than random effects in our analysis (F-test and Breusch-Pagan Lagrange multiplier test also indicated the efficiency of these two basic models when being compared to pooled OLS). We illustrate results estimated using robust standard deviation on the account of heteroskedasticity. The standard errors are reported in parentheses. *, **, *** are designated for the level of significance of 10%, 5% and 1%, respectively.*

Table 2.5 Empirical results of robustness test

	ROA	ROE	NPLR	LPVR
	Sys-GMM	Sys-GMM	Sys-GMM	Sys-GMM
L.	0.387*** (0.067)	0.434*** (0.073)	0.718*** (0.072)	0.388*** (0.148)
L2.	-0.067** (0.027)	-0.083*** (0.031)	-0.140** (0.059)	
1. Large state-owned commercial bank * PKU-DFIIC	**0.164** **(0.135)**	**-2.352** **(2.297)**	**-1.289***** **(0.184)**	**-1.105***** **(0.382)**
2. Joint-stock commercial bank * PKU-DFIIC	**0.157** **(0.135)**	**-2.108** **(2.240)**	**-1.305***** **(0.185)**	**-1.133***** **(0.388)**
3. Urban commercial bank * PKU-DFIIC	**0.105** **(0.133)**	**-2.641** **(2.212)**	**-1.280***** **(0.181)**	**-1.108***** **(0.381)**
4. Rural commercial bank * PKU-DFIIC	**0.106** **(0.133)**	**-2.743** **(2.241)**	**-1.282***** **(0.182)**	**-1.034***** **(0.375)**
_cos	2.418*** (0.764)	43.156*** (11.961)	6.843*** (1.097)	8.921*** (2.898)
Bank-fixed	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes
N	1314	1314	1314	1365
Arellano-Bond test for AR (2)	0.116	0.344	0.126	0.332
Hansen test of overid. restrictions	0.099	0.078	0.109	0.082

*Notes: The present study uses an analyzing power of 10%, which means the null hypothesis (H_0: Digital payment has no impact on the profitability or risk-taking of commercial banks) will be rejected if the t value in the critical region is 5% for each side. The estimation method is the two-step GMM. We conducted an Arellano-Bond test on the second-order residual serial correlation coefficient and Hansen test of over-identified restrictions. We illustrate results estimated using robust standard deviation on the account of heteroskedasticity. The standard errors are reported in parentheses. *, **, *** are designated for the level of significance of 10%, 5% and 1%, respectively.*

Table 2.6 Empirical results robustness test

	ROA	ROE	NPLR	LPVR
	Sys-GMM	Sys-GMM	Sys-GMM	Sys-GMM
L.	0.341*** (0.082)	0.405*** (0.086)	0.764*** (0.076)	0.664*** (0.109)
L2.	-0.077*** (0.026)	-0.086*** (0.031)	-0.164** (0.069)	
1. Large state-owned commercial bank * Digital	**0.017 (0.020)**	**-0.537 (0.376)**	**-0.076 (0.046)**	**-0.131** (0.051)**
2. Joint-stock commercial bank * Digital	**0.006 (0.017)**	**-0.210 (0.281)**	**-0.097** (0.041)**	**-0.148*** (0.042)**
3. Urban commercial bank * Digital	**-0.064*** (0.017)**	**-0.990*** (0.277)**	**-0.101*** (0.036)**	**-0.141*** (0.034)**
4. Rural commercial bank * Digital	**-0.065*** (0.017)**	**-1.051*** (0.275)**	**-0.089** (0.037)**	**-0.082** (0.039)**
_cos	3.516*** (0.524)	34.466*** (5.984)	1.213* (0.626)	2.189 (1.340)
Bank-fixed	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes
N	1314	1314	1314	1365
Arellano-Bond test for AR (2)	0.152	0.426	0.105	0.458
Hansen test of overid. restrictions	0.050	0.015	0.064	0.059

*Notes: The present study uses an analyzing power of 10%, which means the null hypothesis (H_0: Digital payment has no impact on the profitability or risk-taking of commercial banks) will be rejected if the t value in the critical region is 5% for each side. In Panel A, we performed the Hausman test (1978) to choose between the fixed effects model and random effects model, which indicated that the fixed effects model is more efficient than the random effects (F-test and Breusch-Pagan Lagrange multiplier test also indicated the efficiency of these two basic models when being compared to pooled OLS). In Panel B, the estimation method is the two-step GMM. We conducted an Arellano-Bond test on the second-order residual serial correlation coefficient and Hansen test of over-identified restrictions. We illustrate results estimated using robust standard deviation on the account of heteroskedasticity. The standard errors are reported in parentheses. *, **, *** are designated for the level of significance of 10%, 5% and 1%, respectively.*

Appendix 2.1

Table A2.1 Definition of variables

Variables		Definition	Reference
Dependent variables	Return on total assets (ROA in %)	$\mathrm{ROA} = \frac{\text{Profit before tax}}{(\text{Total assets for previous year} + \text{Total assets for current year})/2} \times 100$	Dietrich & Wanzenried, 2011, 2014; Heffernan & Fu, 2010
	Return on total equity (ROE in %)	$\mathrm{ROE} = \frac{\text{Profit before tax}}{(\text{Total equity for previous year} + \text{Total equity for current year})/2} \times 100$	Dietrich & Wanzenried, 2011, 2014; Heffernan & Fu, 2010
	Non-performing loan ratio (NPLR in %)	$\mathrm{NPLR} = \frac{\text{Non performing loan}}{\text{Total various loans}} \times 100$ $\text{Non performing loan} = \text{Subprime loan} + \text{Dubious loan} + \text{Loss loan}$	Albaity et al., 2019; Clark et al., 2018
	Loan provision ratio (LPVR in %)	$\mathrm{LPVR} = \frac{\text{Loan loss provision balance}}{\text{Various loans balance}} \times 100$ $\text{Loan loss provision} = \text{General reserve} + \text{Specialized reserve} + \text{Special reserve}$	Athanasoglou et al., 2008; Anginer et al., 2018; Dietrich & Wanzenried, 2011, 2014 and others
Independent variables	PKU-DFIIC	A holistic index calculated by logarithmic efficacy function from 33 specific indicators of digital financial inclusion. The logarithm of this index is employed in this study.	Guo et al., 2020; Zhao et al., 2022; Xing, 2022; Hu et al.
	Amount of transactions (Digital)	Total transaction (in trillion) through digital payment platforms contains total amounts by both mobile terminal and internet terminal. The logarithm of total transaction is employed in this study.	Xia & Chunsom, 2018

Table A2.2 Continued

Control variables	Liquid assets ratio (Liquidity in %)	$$\text{Liquidity} = \frac{\text{Cash}}{\text{Total assets}} * 100$$	Anginer et al., 2018; Azmi, 2019; Fang et al., 2019; Laeven et al., 2009
	Capital ratio (Capital in %)	$$\text{Capital} = \frac{\text{Equity}}{\text{Total assets}} * 100$$	Albaity et al., 2019; Athanasoglou et al., 2008; Anginer et al., 2018 and others
	Deposits growth rate (Deposit growth in %)	Annual deposits growth rate.	Dietrich & Wanzenried, 2011, 2014
	Operating efficiency (Efficiency in %)	$$\text{Efficiency} = \frac{\text{Operating expenses}}{\text{Operating revenue}} * 100$$ Operating revenue is the revenue gained from the financial products and services provided by the bank, containing net interest income and net non-interest income. Operating expenses is operating-related expenses incurred during business operation.	Albaity et al., 2019; Azmi, 2019; Dietrich & Wanzenried, 2011, 2014; Fang et al., 2019 (SFA) and others
	Fund cost (Fund cost in %)	$$\text{Fund cost} = \frac{\text{Interest expenses}}{(\text{Total deposits for previous year} + \text{Total deposits for current year})/2} * 100$$ Interest expenses is the reward paid to creditor for fundraising in the form of debt by the bank to units and individuals.	Dietrich & Wanzenried, 2011, 2014
	Net interest income ratio (IIR in %)	$$\text{Interest\_income} = \frac{\text{Net interest income}}{\text{Operating revenue}}$$ Net interest income is the difference between the confirmed interest income and the expenses incurred.	Albaity et al., 2019; Azmi, 2019; Dietrich & Wanzenried, 2011, 2014; *Fang* et al., 2019 (non-interest income)
	Bank size (Size)	$$\text{Size} = \ln(\text{Total assets})$$ The nature logarithm of total assets.	Albaity et al., 2019; Athanasoglou et al., 2008; Anginer et al., 2018; Clark et al., 2018 and others
	Major shareholder (Major shareholder in %)	The shareholding ratio of the biggest shareholder.	Laeven et al., 2009
	Bank nature (Nature)	Bank nature is a dummy variable which is 1 for large state-owned commercial bank (6 banks), 2 for joint-stock commercial bank (12 banks), 3 for urban commercial bank (96 banks), and 4 for rural commercial bank (86 banks).	Heffernan & Fu, 2010
	GDP growth rate (GDP growth in %)	Province and prefecture-level annual nominal GDP growth rate.	Azmi, 2019; Dietrich and Wanzenried, 2014; Fang et al., 2019; Fu et al., 2014
	Period dummy variable	The regulation dummy variable is 1 for the accounting period from 2011 to 2013, 2 for the accounting period from 2014 to 2016, 3 for the accounting period from 2017 to 2019, and 4 for 2020 (COVID-19).	

Appendix 2.2

Table A2.2 Variance Inflation Factor

Column A			Column B		
Variable	VIF	$1/VIF$	Variable	VIF	$1/VIF$
PKU-DFIIC	2.33	0.4299	**Digital**	3.21	0.3112
Equity	1.20	0.8314	Equity	1.20	0.8368
Liquidity	1.80	0.5557	Liquidity	2.31	0.4321
Deposit growth	1.09	0.9184	Deposit growth	1.09	0.9158
Efficiency	1.24	0.8041	Efficiency	1.27	0.7865
Interest income	1.06	0.9440	Interest income	1.08	0.9242
Fund cost	1.19	0.8397	Fund cost	1.26	0.7957
Size	1.73	0.5774	Size	1.74	0.5735
Major shareholder	1.38	0.7261	Major shareholder	1.37	0.7311
GDP growth	1.96	0.5095	GDP growth	1.98	0.5053
Mean VIF	1.50		Mean VIF	1.65	

Notes: VIF in Column A is calculated to identify multicollinearity when estimated with PKU-DFIIC. VIF in Column B is calculated to identify multicollinearity when estimated with total transaction through digital payment platforms. A higher VIF for a variable indicates a high degree of linear relationship to other regressors. In the present study, a VIF above 5 indicates high multicollinearities.

3 The Impact of Technology-Driven M&A on Bank Opacity, Stock Price Synchronicity, and Risk Composition: Empirical Evidence from Japan and a Causality Analysis

3.1 Introduction

In the face of the escalating influence of financial technologies, incumbent banks are responding in diverse ways (Drasch et al., 2018). Confronted with limited budgets and modest internal innovation capabilities, these banks frequently seek external technologies (Austin & Dunham, 2022; Carlini et al., 2022) and employ strategies such as business alliances, incubation, acceleration, joint ventures, and acquisitions (Austin & Dunham, 2022; Drasch et al., 2018; Hornuf et al., 2021). Prior research has explored the impact of technology-driven M&As on innovation performance (Cloodt et al., 2006; McCarthy & Aalbers, 2016), profitability, liquidity (Akhtar & Nosheen, 2022), as well as risk profiles (Austin & Dunham, 2022), most of which yields a positive relationship between technology engagement and firm performance. Event studies analyzing the market response to these technology-driven investment have presented a mixed picture, with some studies indicating positive results (Dranev et al., 2019) and others reporting negative effects (Cappa et al., 2022; Carlini et al., 2022; Hornuf et al., 2021). Despite the extensive body of research, a noticeable gap exists in comprehending how technology-driven M&As influence bank opacity, an inherent phenomenon within banking industry (Akhigbe & Martin, 2006; Morgan, 2002).

Opacity in the banking industry creates challenges for external stakeholders in assessing asset value (Akhigbe & Martin, 2006; Morgan, 2002). It also complicates the accurate evaluation of insiders' risk-taking (Bushman, 2014; Flannery et al., 2004, 2013; Jones et al., 2012, 2013). What's more, this opacity undermines market discipline on bank actions by reducing external monitoring, contributing to both price delay and market inefficiency, and exacerbating the speculative cycles of both bubbles and crashes (Blau et al.,, 2017; Bushman, 2014; Jones et al., 2012, 2013; Zheng, 2020). Numerous approaches exist for assessing bank opacity, and multiple studies (Flannery et al., 2004, 2013; Jones et al., 2012; Livingston et al., 2007; Morgan, 2002) agree that the absence of transparency in banks primarily results from asset composition, especially loans, trading assets, and loan loss provisions that carry concealed risks. Thus, this study investigates the impact of technology-driven M&As on bank opacity from a perspective of asset structure. In this context, bank opacity is measured by the absolute value of the residuals in the regression model of loan loss provision.

The perspective emphasizing a complementarity relationship between incumbent banks and technology firms is borne out by improved operating efficiency, competitive ability, and corporate performance via knowledge synergies (Austin, & Dunham, 2022; Cappa et al., 2022; Dranev et al., 2019; Kogut & Zander,1992; Ma & Liu, 2017). Additionally, risk diversification is achieved by diversifying asset composition through M&As in accordance with portfolio theory (Berger et al., 1999). The diversification of risk is further facilitated by the expansion of investment opportunity set driven by technological advancements. Thus, risk diversification reduces the information asymmetry between insiders and outsiders, thereby decreasing bank opacity. Additionally, both the enhanced performance and accurate income prediction through technologies diminish the income smoothing motive for recognizing loan loss provisions. Conversely, the substitution effect and disruption innovations can be inferred from the inherent riskiness of the high-tech industry (Cappa et al., 2022; Dranev et al., 2019; McCarthy & Aalbers, 2016). The potential failure of M&As increases the income smoothing motive for recognizing loan loss provisions and amplifies information asymmetry. The intensification of opacity is additionally heightened by the accumulation of goodwill through M&As (Xie et al., 2020), which is the surplus of fair value in a business acquisition and the actual value of which disclosed by enterprises may not be accurately represented because of the limited information disclosure and various measurement methods (Kwon & Wang, 2023; Xie et al., 2020). In this vein, our research question is whether technology-driven M&As increase or decrease bank opacity.

Our study exclusively examines Japanese acquirers, specifically Japanese firms categorized as either listed banks, or non-listed banks but belong to listed banking parent companies such as financial groups (hereafter Japanese-listed banks). We concentrate on the entire sample period from 1996 to May 2023 in the database, covering 1,165 M&A transactions involving 163 banks, of which the targets are further classified into 40 industries. Out of these, 461 transactions have been matched with bank financial data and the retained data spans the period from April 1999 to March 2022. Although the sample size is limited, it represents the most comprehensive compilation of M&A activities conducted by Japanese-listed banks available to us. The companies that were not merged with our dataset were excluded due to various reasons, such as certain banks being delisted or acquired. We identify M&A transactions as technology-driven if the target company operates in the software and information sector. This categorization has been substantiated through a meticulous check of M&A transcripts. Summarizing the industry distribution of target company, we discovered a new wave of M&As between banking organizations and entities in the software and information, other types of financial service providers as well as services industry (Table 3.1). To assess the average treatment effects (*ATT*) on the treatment group, we employed both propensity score matching (PSM) and differences-in-differences PSM (DID-PSM) analysis. Our findings offer compelling evidence that technology-driven M&A transactions exhibit a negative association with bank opacity, which is particularly pronounced for foreign technology-driven M&As that is transaction involving a Japanese-listed banking acquirer and foreign technology target. This result remains robust across various econometric techniques, and alternative outcome variables.

We propose that reduced bank opacity enhances stock price informativeness. Previous studies suggest that low stock synchronicity may result from informed arbitrageurs integrating private information or occasional market noise (Roll, 1988; Morck et al., 2000; Durnev et al., 2003). Opaque stocks are also prone to experience sharp declines, leading to substantial negative returns (Jin & Myers, 2006). However, subsequent research presents contradictory viewpoints. In more transparent environments, stock prices are expected to offer greater insight into future events and higher synchronicity. Therefore, less opaque stock today indicates higher return synchronicity in the future (Dasguapta et al., 2010). Our research then explores stock price synchronicity and informativeness dynamics, especially when bank opacity is reduced through technology-driven M&A activities. Another consequence of the change in opacity is the alteration of risk composition, as increased transparency enhances the reliability of firm-specific information and refines the idiosyncratic component of risk.

We calculate bank-quarter stock price synchronicity, betas and idiosyncratic risk using the market model with daily equity returns and the TOPIX index as the market proxy from January 4, 1999 to June 30, 2022. Estimated results showed that bank's involvement in technology-driven M&As results in decreased stock price synchronicity and betas, with no significant change observed for idiosyncratic risk. This finding holds consistently when applying different econometric methods including PSM and DID-PSM analysis, employing alternative market index such as Nikkei 225, and considering alternative treatment variables. Opacity in financial markets can erode information efficiency, leading to increased price synchronicity and a greater susceptibility to systemic market failure (Jones et al., 2012). Consequently, we also conclude that technology-driven M&As have the potential to diminish susceptibility to systemic market failure and enhance stock market stability.

Our study contributes to prior research in several ways. First, we provide empirical evidence confirming the positive relationship between bank transparency and technology-driven M&As. Goodwill in M&A activities is identified as a factor that increases bank opacity. However, we have identified a potential tradeoff, as the acquisition of technologies enhances transparency by improving bank performance and diversifying asset risk.

Second, we deepen the understanding of the relationship between technology-driven M&As with both stock price synchronicity and stock risk composition. While many studies underscore that the convergence of the financial industry with other sectors raises concerns by introducing external factors into the banking sector, posing risks that could threaten the stability of the financial system, our research offers additional evidence. We provide additional evidence that technology-driven and knowledge-oriented M&As may benefit incumbent banks through knowledge synergy, reducing bank opacity and contributing to stock market stability. Our findings provide policymakers with insights into whether to permit financial institutions to engage in M&A activities in non-financial sectors.

This chapter is structured into 6 sections. Section 3.2 presents an overview of relevant literature, discussing bank opacity, technology-driven M&As, stock price informativeness and synchronicity. In section 3.3, we detail our methodology, including the empirical models and descriptive statistics. Empirical results of PSM analysis and DID-PSM analysis are reported in Section 3.4, which is flowed by a further analysis of stock price synchronicity and risk composition in Section 3.5. Finally, we conclude and provide a further discussion in Section 3.6.

3.2 Literature review

3.2.1 Bank opacity

Opacity, a phenomenon within the banking industry (Akhigbe & Martin, 2006; Morgan, 2002), hinders the assessment of asset value by external stakeholders like shareholders and creditors, while complicating the accurate evaluation of risk-taking by insiders such as managers (Bushman, 2014; Flannery et al., 2004, 2013; Jones et al., 2012, 2013). Prior literature adopts various measures to quantify bank opacity, including bid-ask spread, Amihud's illiquidity of bank stock (2002), frequency and magnitude of split bond ratings[11], and analysts' earnings forecasts variability (Flannery et al., 2013; Jone et al, 2012; Livingston et al, 2007; Morgan, 2002). For instance, Morgan and Stiroh (2001) proposed that risker activities like trading, credit card, and lending correlate with higher bond spreads. Similarly, Jones et al. (2013) emphasized that market return contemplates investments in opaque assets of banks because of their risk-taking behaviors.

In a perfectly competitive market, risks linked to opacity are accurately evaluated by market participants, enabling an efficient distribution between opaque and transparent assets (Bushman & Williams, 2012), which is conceptualized as a process of market discipline. The effectiveness of market discipline depends on investors' ability to access timely and credible information about firms and to make appropriate decisions based on the gathered information (Bushman & Williams, 2012; Flannery et al., 2004). However, opacity undermines market discipline on bank action by both attenuating external monitoring and amplifying the speculative cycles of bubbles and crashes (Bushman, 2014; Jones et al., 2012, 2013; Zheng, 2020). Investigating the relationship between price contagion and bank opacity in the period of 2000 to 2006, Jones et al. (2012) found banks undergoing lower revaluation surrounding merger announcements emulated banks that invested more in opaque assets but were positively

[11] Moody's and S&P split.

revaluated. Furthermore, they observed that less transparent banks during normal periods endured larger price reversals during the financial crisis of 2007 to 2008. In their another work, Jones et al. (2013) also suggested that the reduction of valuation discounts on opaque assets coincided with an increase in bank equity share prices and a decrease in transparent assets. This feedback effect that promotes other banks to invest more in opaque assets, exacerbates risk concentration and instability of the financial system. Extant literature also provided evidence that opacity contributes to price delay and market inefficiency because higher bid-ask spread, stock illiquidity, and real estate loans to total assets are associated with increased price delay (Blau et al., 2017).

Multiple scholarly investigations corroborate that the lack of transparency in banks primarily emanates from specific assets, notably loans and trading assets. These assets carry hidden risks that are difficult to detect or subject to easy manipulation. Morgan (2002) explored the relationship between banks' asset composition and the bond splits (rating splits between Moody's and S&P) of 7,862 new bonds issued between January 1983 and July 1993. They discovered a heightened frequency of split ratings for financial intermediaries (bank and insurance firms), with the uncertainty attributed to banks' asset composition. Livingston et al. (2007) extended Morgan's asset opaqueness hypothesis (2002) by encompassing non-banking firms and demonstrating that asset opaqueness also leads to split ratings for non-bank firms. They also established the persistency of split ratings, indicating the inherent difference between split-rated bonds and non-split-rated bonds. Additionally, Flannery et al. (2004) proved that bank holding companies' (BHCs) asset composition significantly predicts the analysts' earnings forecasts variation, supporting the notion of divergent opacity arising from BHCs' assets. In a separate study (2013), they also showed that from 1993 to 2009, a bank's equity opacity increased in real estate loans by adopting an effective bid-ask spread. Consequently, lucid corporate disclosures in published financial statements and mandatory filings play a critical role for shareholders and other stakeholders in the assessment of firm valuation (Akhigbe & Martin, 2006).

In addition to loans and trading assets, another component of the balance sheet that is discretionary and reflects information properties of banks' financial reports, is the loan loss provisions. This provision plays a pivotal role in accounting decisions in terms of risk embedded within loan portfolios, directly impacting the volatility and cyclicality nature of bank earnings, as well as information asymmetry (Bushman & Williams, 2012; Bushman, 2014). Banks possess diverse motives for determining discretionary loan loss provisions. Delaying the recognition of expected loan losses in the current provision (DELR) can be interpreted as an opportunistic loan provisioning conduct (Bushman, 2014), which impairs the transparency of banks. Huizinga and Laeven (2019) summarized that bank managers establish provisions during periods of relatively high profits and tap into loan loss reserves when actual losses surpass anticipated losses (referred to as income smoothing motive), or accelerate provisions for loan expansion because banks experiencing rapid loan growth often challenges in preserving consistent credit standards (referred to as risk-taking motive), or strategically align loan loss provisions vis-à-vis regulatory capital requirements (referred to as capital management motive). These motives and the accuracy of disclosed loan loss provisions bear significance in terms of information quality and investor uncertainty over banks' fundamentals. Prior research (Jiang et al., 2016; Zheng, 2020) has also utilized the absolute and negative residuals after regressing loan loss provision to a series of factors, to gauge bank opacity.

Just as the Glass-Steagall Act of 1934 in response to bankers' misconducts that leads to the 1929 market crash, the Sarbanes-Oxley laws (SOX) of 2002 to fraudulent accounting scandals that result in massive corporate collapses, and the Dodd-Frank Act of 2009 followed the high-level mortgage-backed securities (MBS) that bring about 2008 world financial crisis, regulatory laws are designed and enacted to increase market efficiency, foster financial stability, and prevent future systemic risks. Existing literature also delves into exploring the interrelation between novel legislations or investor rights, and the level of opacity in banking institutions. Akhigbe and Martin (2006) underscored that the implementation of SOX enhances industry transparency and benefits the financial services industry significantly. Jirasakuldech et al. (2011) heightened the correlation between strong investor rights with reduced market risk, promoted mean-variance efficiency, and diminished capital costs for firms.

In summary, bank opacity, which can be assessed from the perspective of asset structure, is a factor hindering marker efficiency, and a subject that policymakers may want to improve.

3.2.2 Technology-driven M&As in the banking industry

In response to the emergence of financial technology trends, prior research (Austin & Dunham, 2022; Carlini et al., 2022) has emphasized that banks without substantial budgets or internal innovation capabilities tend to adopt external or open innovation approaches. Additionally, research (Drasch et al., 2018; Hornuf et al., 2021) has presented different frameworks illustrating how banks and fintech firms cooperate in innovation efforts, including business alliances, incubation and acceleration, joint venture as well as acquisition. The potential dynamics between technology firms and incumbent banks encompass various scenarios, such as substitution and disruption effect versus complementarity and collaborations effect (Drasch et al, 2018), or potential growth hypothesis versus integration failure hypothesis in other words (Dutta & Kumar, 2009).

Two streams of research support the idea of complementarity, collaboration, and potential growth. First, M&As involving technology companies (technology-driven M&As) offer a strategic avenue for achieving knowledge synergies (Cappa et al., 2022; Dranev et al, 2019), improving operating efficiency, entering new sectors (Ma & Liu, 2017), and building future competitive advantages (Austin, & Dunham, 2022; Kogut & Zander,1992). Furthermore, for traditional commercial banks, the integration of the merged companies, when compared to other forms of investment like credit lines, confers ownership control, potentially facilitating the smooth assimilation of strategic resources. These innovations hold the possibility of enhancing bank performance through competitive edges, efficiency enhancements, and risk mitigation. Noteworthy empirical studies corroborate this view. A study by Cloodt et al., (2006) provided empirical evidence that technological acquisitions enhance short-term innovation performance, contrasting with non-technological M&As which have a negative effect. McCarthy and Aalbers (2016) established that technological acquisitions lead to increased patent applications, as they foster economies of scale and scope, and augment a firm's ability to assimilate and develop knowledge. Another study by Akhtar and Nosheen (2022) demonstrated that mergers between financial technology and banks positively predict acquirers' profitability measured by ROA and liquidity position indexed by current ratio.

Second, in accordance with portfolio theory, banks could construct a diversified asset portfolio via technology-driven M&As, resulting in reduced concentration both in terms of geographical scope and industrial sectors (Berger et al., 1999). The diversification of risk is further facilitated by the expansion of investment opportunity set driven by technological advancements. Analyzing the post-acquisition performance from 2010 to 2017 in the US, Austin and Dunham (2022) validated that acquirers' risk profiles measured by stock price volatility is improved notably. But there was no evidence that operational performance, in terms of cash flow and ROA, was enhanced after the acquisition on technologies.

The proponent of the substitution disruption effect, and integration failure hypothesis originates from the intrinsic riskiness of the high-tech industry, the acquisitions of which are known to carry complexities and potential disappointments. Due to the heightened risk profile of this sector, takeovers could possibly cause significant disruptions to a company's fundamental business operations (Cappa et al., 2022; Dranev et al., 2019; McCarthy & Aalbers, 2016). In research that categorized 1,078 observations of technology investment into financial-native and tech-native subgroups, Bellardini et al. (2022) revealed that banks tend to favor financial-native companies in contrast to tech-native counterparts because of perceiving greater security in the former.

The deepening of opacity is further accentuated by the accrual of goodwill through M&As. The leftover after subtracting fair value of the identifiable assets and liabilities acquired in a business combination is separately recorded as goodwill. This value of goodwill is linked to elements like customer loyalty, off-balance-sheet activities, and other related factors that are difficult to measure but are often the primary motives of M&As (Kwon & Wang, 2023). More specificity, goodwill captures the synergy arising from M&As, bearing predictive significance for the long-term success of business combinations (Li et al., 2011). Nevertheless, due to the opacity of M&A information disclosure and variations in goodwill measurement methods, the actual value of goodwill disclosed by enterprises may not be accurately represented (Xie et al., 2020). Consequently, technology-driven M&A transactions could also potentially contribute to an increase in bank opacity.

A flurry of research papers has examined the response of market to technology-driven M&As using an event study methodology, yielding disparate findings. Dranev et al. (2019) investigated financial technology acquisitions from 2010 to 2018 across the USA, Canada, Europe, China, and India. They found a significant positive average abnormal return in the short term but a negative average abnormal return in the long term. Conversely, testing the stock returns subsequent to collaboration announcements across Canada, France, Germany, and the United Kingdom, Hornuf et al. (2021) observed negative effects on cumulative abnormal returns (CAR) when the news is given to the market. Consistent findings are reported by Cappa et al., (2022) and Carlini et al. (2022). The acquisitions of the digital payment sector are negatively related to CAR in the European and US context (Cappa et al., 2022), while the negative effect is stronger for younger firms and in the case of multiple investments (Carlini et al., 2022). This body of empirical evidence emphasized that the benefits from technology companies can be balanced by the challenges of integrating different business models, leading investors to view technology or fintech firms with limited financial ties as high-risk investments.

Within the existing research, there has been a notable gap in examining whether technology-driven M&As affect the bank opacity. The improved performance and precise income prediction facilitated by technology decrease the motivation for income smoothing in recognizing loan loss provisions. Furthermore, risk diversification diminishes information asymmetry between insiders and outsiders, leading to a reduction in bank opacity. Conversely, the potential failure of M&As intensifies the motivation for income smoothing in recognizing loan loss provisions and the accrual of goodwill exacerbates information asymmetry. Hence, our research that there may be both a positive and negative relationship between technology-driven M&As and bank opacity.

H3.1a: *Technology-driven M&As negatively predict bank opacity.*

H3.1b: *Technology-driven M&As positively predict bank opacity.*

3.2.3 Stock price synchronicity

Stock price synchronicity has been well-established in previous studies, with a plethora of research exploring the connection between stock price synchronicity and informativeness. In this study, we are more curious about whether stock price synchronicity changes following technology-driven M&As. We postulate that stock price will be more informative when bank opacity is reduced. However, there are conflicting arguments emerging regarding the relationship between stock price informativeness and synchronicity.

Some studies have concluded that low stock synchronicity may be attributed to either the integration of private information facilitated by actively informed arbitrageurs or occasional market frenzy such as noise (Roll, 1988; Morck et al., 2000; Durnev et al., 2003). Morck et al. (2000) discovered that stock prices in high-income countries exhibit lower synchronicity compared to their counterparts in low-income countries, primarily due to the stronger protection of private property rights in high-income countries that encourage informed trading as well as the existence of anti-director rights that enhance the utility of firm-specific information for risk arbitrageurs. Nevertheless, political events and rumors in low-income economies can trigger widespread fluctuations, which results in suboptimal capital allocation and hamper economic growth. Durnev et al. (2003) observed that a higher level of firm-specific stock return variation is related to more informative stock prices, while the price informativeness is measure by the extent to which stock prices encapsulate information about future earnings. Moreover, the greater complexities in understanding a firm with higher opacity, may deter informed trading by increasing the costs associated with informed arbitrage. Opaque stocks are also prone to experience sharp declines, leading to substantial negative returns (Jin & Myers, 2006).

Subsequent research has presented contradictory viewpoints. Stock prices in more transparent environments are expected to offer greater insight into future events and higher synchronicity, because when events occur in the future, there should be less surprising and less new information being factored into the stock price. Therefore, a more informative stock price today indicates higher return synchronicity in the future (Dasguapta et al., 2010). Piotroski and Roulstone (2004) discovered that return synchronicity increases in analyst converge that indicate more industry-wide and market-wide information being incorporated into stock prices. This interpretation is borne out by other studies as well. For instance, Chan and Hameed (2006) examined data from emerging markets and reported that greater analyst coverage leads to higher return synchronicity. What's more, Barberis et al. (2015) proved that the inclusion in the Standard and Poor's (S&P) 500 index, which presumably enhances firm-level transparency, increases a stock's return synchronicity. Taking the implementation of the regulation as an opportunity, prior research has also analyzed the relationship between disclosure related regulation and stock prices synchronicity. Employing a differences-in-differences (DID) analysis, Kan and Gong (2018) conducted a study to assess the effects of a Regulation SHO pilot program announced by Securities and Exchange Commission (SEC) on July 28, 2004. This program removed short-selling price tests for randomly selected stocks (referred to as "pilot stock") and probably contributed to stock price discovery and efficiency. The results indicate that, relative to non-pilot stock, pilot stocks experienced a notably greater increase in both price informativeness and return synchronicity when the pilot program was initiated. What's more, Abedifar et al. (2021) examined the effects of a new Small Banking Holding Company (BHC) Policy Statement announced by Federal Reserve in May 2015. This statement aims to reduce regulatory burdens imposed on small banks. The analysis using a regression discontinuity design (RDD) analysis provided evidence that a decrease in return synchronicity corresponds to a decrease in stock price informativeness. Banerjee et al. (2018) reconciled stock price informativeness and synchronicity by emphasizing that increased public disclosure can have a dual effect. It can both suppress private learning about fundamentals while also encourage more learning about the beliefs held by other investors and displace private learning about fundamental factors. As a result, when the relative rate of information acquisition about fundamental factors lags behind, the informativeness of stock prices of stock prices regarding those fundamentals may decrease despite increased information disclosure and transparency.

Our research topic provides an opportunity to delve into the dynamics of stock price synchronicity and informativeness, particularly when the bank opacity is attenuated through technology-driven M&A activities. Few scholars have paid attention to the impact of M&As on stock price synchronicity and risk composition. Xie et al. (2020) employed data from Chinese A-listed companies spanning the period 2008 to 2016 to examine the correlation between M&A goodwill and stock price crash risk. Their findings revealed that companies involved in goodwillgenerating M&As faced an elevated risk of future stock price crashes. In line with Jin and Myers (2006), we hypothesize that bank stock price synchronicity will diminish in the context of technology-driven M&As if bank opacity decreases, because reduced opacity will encourage informed trading and incorporates more private information into stock price.

H3.2a: *Technology-driven M&As negatively predict stock price synchronicity.*

H3.2b: *Technology-driven M&As positively predict stock price synchronicity.*

Another consequence of the change in opacity is the alteration of risk composition, as increased transparency enhances the reliability of firm-specific information and refines the idiosyncratic component of risk (Morck et al., 2000). Therefore, we hypothesize that the bank stock beta decreases, while the idiosyncratic risk increases, in response to changes in bank opacity and stock price synchronicity.

H3.3a: *Technology-driven M&As negatively predict beta, while positively predict idiosyncratic risk.*

H3.3b: *Technology-driven M&As positively predict beta, while negatively predict idiosyncratic risk.*

3.3 Methodology

3.3.1 Measuring bank opacity

The measure for bank opacity is motivated by the concept of information asymmetry between bank insiders (such as managers) and outsiders (such as investors). Bank managers possess more insights and more information compared to investors and creditors. For instance, loan loss provisions are account entries that serve as precautionary funds against potential losses from credit defaults and represent the ambiguity within bank assets. Bank managers can use their information advantage to set discretionary loan loss provisions for income-smoothing motive, risk-taking motive, and capital management motive (Huizinga & Laeven, 2019), which reduces the informativeness of financial reports and creates opacity in bank operations. Therefore, we follow the methodologies of Jiang et al. (2016) and Zheng (2020) by constructing a panel regression model (formula 3.1) with loan loss provision (LPV) as the dependent variable, and an array of bank characteristics as explanatory variables. The covariates contain loans ratio ($Loans$), non-performing loans ratio ($NPLR$), as well as the lagged ($L.NPLR$) and forward ($F.NPLR$) non-performing loans ratio. This model explains how the disclosed factors ($Loans$, $NPLR$, $L.NPLR$) and predicated $NPLR$ ($F.NPLR$ serve as bank's predication) forecast loan loss provision for a bank.

In the following equation (formula 3.1), i represents the bank, and t indexes time. μ_i is the unobservable individual-specific effects, while λ_t is the time-specific effect of each model. ϵ_{ijt} denotes the stochastic disturbance with IID, the absolute value of which (formula 3.2) is adopted as the measure to gauge the level of vagueness and capture the informativeness position of the banks' financial statements (informativeness opacity) in the present study. A higher absolute value indicates a higher degree of opacity in bank's financial statements. In prior studies, negative residuals are employed as the dependent variable in the robustness test. The positive value of the error term in this model tends to represent transparent banks' overestimation of future loan loss. By using negative residuals, we can focus on banks that underestimate expected loan losses, potentially indicating a higher level of opacity. Consequently, the alternative measure involves taking the absolute value of negative residuals (formula 3.3) and setting 0 for non-negative residuals (formula 3.3').

Fixed effects model

$$LPV_{it} = \beta_1 * Loans_{it} + \beta_2 * NPLR_{i,t-1} + \beta_3 * NPLR_{it} + \beta_4 * NPLR_{i,t+1} + \lambda_t + \mu_i + \epsilon_{it} \quad (3.1)$$

Measuring bank opacity: absolute value of residuals

$$Opacity\_Absolute_{it} = \frac{|\epsilon_{it}|}{Total\ Assets_{it}} \times 100 \quad (3.2)$$

Alternative measure of bank opacity: absolute value of negative residuals

$$Opacity\_Negative_{it} = \frac{|\epsilon_{it}|}{Total\ Assets_{it}} \times 100 \ \ for \ \ \epsilon_{it} < 0 \quad (3.3)$$

$$Opacity\_Negative_{it} = 0 \ \ for \ \ \epsilon_{it} \geq 0 \quad (3.3')$$

3.3.2 Quantifying the treatment effect of technology-driven M&As

$$(Opacity\_Absolute_{0i}, Opacity\_Absolute_{1i}) \perp Target\_Software_i | x_i \quad (3.4)$$

To evaluate the average treatment effect of technology-driven M&As on the treated (ATT), propensity score matching (PSM) as introduced by Rosenbaum and Rubin (1983) can be adopted when randomized controlled trial (RCT) is not feasible and necessitating causal inference from non-experimental data. The treatment group consists of M&A activities involving target industry that belongs to software and information ($Target\_Software$). Additionally, we conducted robustness tests using transactions involving a target within the software and information sector or those M&A transcripts that include discussions on topics such as "financial technology, payment, cashless, information technology, technology, big data, and innovation" ($Target\_Tech$). Other M&As are included in the control group. In the context of PSM analysis, it is assumed that all relevant covariates influencing treatment assignment have been observed and incorporated into the model, following the conditional independence assumption (CIA, formula 3.4). In the formula (3.4), the treatment variable for individual bank i is $Target\_Software_i$, which is 1 for technology-driven M&As and 0 for others. The outcome of interest is the opacity of treatment group ($Opacity\_Absolute_{1t}$) and control group ($Opacity\_Absolute_{0i}$). To ensure compliance with the ignorability assumption, we control for bank-related and M&A-related characteristics (x_i), including bank size ($Size$), deposit growth ratio ($Deposit\ growth$), capital ratio ($Capital$), interest income ratio (IIR), return to assets (ROA), foreign M&A ($M\&A\_Foreign$), and M&A classification ($M\&A\_Classify$). The definitions of all variables used in the current study are summarized in Table A1, and the top and bottom 1% of the banking data are winsorized. We employ logistic regression to estimate the propensity scores.

Kernel matching

$$\omega(i,j) = \frac{K\left[\frac{x_j - x_i}{h}\right]}{\sum_{k:Target\_Software_k=0} K\left[\frac{x_k - x_i}{h}\right]} \tag{3.5}$$

$$\hat{y}_{0j} = \sum\nolimits_{j:Target\_Software_j=0} \omega(i,j)\, y_j \tag{3.6}$$

The initial matching method employed is kernel matching, as introduced by Heckman et al. (1997), Kernel matching assigns banks to the treated (i) and comparison group (j) while taking into account the entire distribution of propensity scores. This approach (formula 3.5) utilizes a kernel density function, denoted as $K(\cdot)$, with a specified bandwidth parameter (h) to determine the weights ($\omega(i,j)$). We use the default Epanechnikov kernel along with a default bandwidth of 0.06. The kernel regression estimator is computed using formula (3.6).

Caliper matching

$$|p_i - p_j| \le \varepsilon = 0.25\hat{\sigma}_{pscore} \tag{3.7}$$

We also employ caliper matching analysis, which constrains the matching process by setting a predetermined "caliper" width. Pairs of treated (i) and control (j) units are matched only if their propensity scores fall within this caliper width (ε), as indicated in formula (3.7). A narrower caliper results in stricter matching, while a larger caliper allows for more flexibility. In our analysis, we set the caliper at 0.01 ($< 0.25\hat{\sigma}_{pscore}$), which is more stringent compared to the common practice of using the caliper at one-quarter of the standard deviation of propensity scores ($0.25\hat{\sigma}_{pscore}$).

Nearest-neighbor matching within caliper

Within the former caliper, the k-nearest matching is also applied. For each treated individual, the algorithm identifies control individuals whose propensity scores are the closest to the treated individual's propensity score without exceeding the caliper width. Depending on the caliper width and the distribution of propensity scores, a treated individual may be matched with multiple control individuals if they fall within the caliper range. Exact matching (one-to-one matching) minimizes bias but increases variance, whereas inexact matching (one-to-more) reduces variance but increases bias. As a general practice, we perform one-to-four matching to minimize mean squared error (MSE).

We waived Mahalanobis matching due to its challenges when dealing with an excessive number of covariates and insufficient sample size. Data balance is assessed following each matching procedure.

Differences-in-differences propensity score matching analysis (DID-PSM)

$$\widehat{ATT} = \frac{1}{N_1}\sum_{i:i\in I_1 \cap S_p}\left[\left(y_{1i,t+1} - y_{1i,t-1}\right) - \sum_{j:j\in I_0 \cap S_p}\omega(i,j)\left(y_{0i,t+1} - y_{0i,t-1}\right)\right] \quad (3.8)$$

The assumption of ignorability in PSM analysis is a stringent precondition and demands a rich set of covariates. To address the endogeneity arising from immutable unobservable variables, we employ the DID-PSM approach to mitigate the effects of these covariates using panel data (Heckman et al, 1997). We utilize kernel matching along with default Epanechnikov kernel to match the treated and control group and estimate the average treatment effect on the treated (ATT) use formula (3.8). S_p represents the common support, while I_1 denotes the treated, and I_0 signifies the comparison group. N_1 is the count of observation in the intersection $I_1 \cap S_p$. $\omega(i,j)$ is weighting function, as described in formula (3.5). $y_{1i,t+1} - y_{1i,t-1}$ represents the change in outcomes for the treatment group from before technology-driven M&A ($t-1$) to post-acquisition ($t+1$), while $y_{0i,t+1} - y_{0i,t-1}$ signifies the change in outcomes for the control group during the same period.

3.3.3 Data and descriptive statistics

We concentrate on the entire sample period from 1996 to May 2023 in the database, covering 1,165 M&A transactions involving 163 banks. Among these, 461 transactions have been matched with bank financial data based on the Japanese fiscal year[12], encompassing the time frame from April 1999 to March 2022. Our study focuses exclusively on Japanese acquirers, specifically Japanese firms that are either listed banks or the non-listed banks but with listed banking parent companies (financial group). Although the sample size is limited, it represents the most comprehensive compilation of M&A activities conducted by Japanese-listed banks that are available to us. The transactions that were not merged with our dataset were excluded due to various reasons, such as certain banks being delisted or acquired. Table 3.1 provides an overview of the industry distribution of targets. 461 M&A transactions are categorized into 40 industries that is established basing the Tokyo Securities Exchange 33-industry classification.

Financial technology includes elements such as big data, artificial intelligence, cloud computing, and cybersecurity solutions, all of which have their origins in the

[12] For instance, M&A activity in March 2021 is merged with financial data from the fiscal year 2021, whereas M&A activity in April 2021 is merged with the fiscal financial report data from 2022.

IT sector. Thus, we have identified M&A transactions as technology-driven if the target company operates in the software and information sector. We also substantiated this categorization through an examination of M&A transcripts. Notably, there is a discernible upward trend in M&A activities involving targets belong to software and information, along with other financial businesses sector and services industry, while there is a simultaneous decline in M&A transactions involving targets in banking industry.

Table 3.2 illustrates the distribution of retained M&A targets among different types of banks. Since 2015, all banks have undergone numerous technology-driven M&As. In the unreported summarization, we observed that this trend has persisted up to the time of our data collection (May 2023). Notably, new types of banks, such as online banks, have experienced a significantly higher frequency of technology-driven M&As compared to other banks. There is little variation in the frequency of technology-driven M&As among city banks, regional banks, and secondary regional banks.

Table 3.3 presents the distribution of M&A targets in two specific categories: $Target\_Tech$ (referring to an alternative measure for technology-driven M&As) and $M\&A\_Foreign$ (indicating foreign M&A). $Target\_Tech$ represents broader definition of technology-driven M&As by encompassing transactions with targets in the software and information sector or those where M&A transcripts include discussions related to relevant topics such as financial technology, payment, cashless, information technology, big data, and innovation. This definition excludes discussion on "technology" specifically related to environmental protection technology. Notably, there are 3 more technology-driven M&A deals compared to the count within the software and information sector ($Target\_Software$). Foreign M&A refers to transactions where Japanese acquirers engage with foreign targets. Table 3.3 underscores a rising trend in technology-driven M&A activities and reports an anticipated increase in foreign M&A transactions in the near future.

Descriptive statistics for all variables are presented in Table 3.4. There are 13.4% M&As involve targets in the software and information sector among our dataset, while broadly 14.1% are classified as technology-driven M&A ($Target\_Tech$). Additionally, 14.5% of the M&A transactions involve foreign targets. Our sample encompasses M&A and M&A-related transactions, which are categorized into five distinct classes. These categories are identified using a dummy variable ($M\&A\_Classify$), with a value of 1 indicating M&A, 2 for intra-group M&A, 3 for subsidiary acquisition (including 100% acquisition and subsidiary share repurchase), 4 for spin-off and division, and 5 for holding company transactions. To gauge the frequency of M&A transactions and foreign M&A transactions within our panel data analysis (DID-PSM), we calculated these frequencies within specific timeframes, such as one year. The maximum values for $Sum\_M\&A$ and $Sum\_Foreign\_M\&A$ indicate that the most active banks engage in M&A activities up to 10 times within a year and conduct foreign M&A transactions up to 6 times within a year.

Financial data from the banking sector covering the period from 1999 to 2023 and stock market data over the period from January 4, 1999 to June 30, 2022 have been sourced from the NEEDS FinancialQUEST database. We restricted our sample to banks with at least 3 years of financial statement data, resulting in a total sample of 74 commercial banks and 1,362 observations. By regressing formula (1), we obtained the predicated opacity measure, $Opacity\_Absolute$ and $Opacity\_Negative$. Our first measure for bank opacity, $Opacity\_Absolute$, has a mean value of 3.14% and exhibits a volatility of 4.49%. The alternative measure for bank opacity, $Opacity\_Negative$, has a mean value of 2.88% and a volatility of 4.47%. On average, loans account for 62.81% of banks' assets, with the highest recorded value being 77.13%. Additionally, an average of 3.96% of total loans is classified as non-performing loans. Non-performing loans in Japan are categorized and defined in accordance with the Financial Reconstruction Act (FRA), with these loans are further divided into special attention loans, doubtful loans, and bankrupt/de facto bankrupt loans. To address missing values, we explore alternative methods such as utilizing data on risk-monitored loans as measured by the Financial Services Agency (FSA) in Japan. It's noteworthy that all other covariates have been verified to fall within reasonable value ranges[13]. Before performing the regression analysis, the variance inflation factor (VIF) is calculated to identify the amount of multicollinearity among our regressors. Estimated VIF shows no existence of high multicollinearities.

[13] In this study, the minimum value of the capital adequacy ratio is below the 4% baseline specified by the Financial Services Agency in Japan. This discrepancy may be attributed to the scaling of net assets by total assets rather than using risk-weighted assets.

3.4 Empirical results

3.4.1 PSM analysis

We initiated our analysis by merging the M&A dataset with the dataset containing financial information from banks. This amalgamation yielded a dataset comprising 461 observations. Table 3.5 to 3.7 present the ATT of technology-driven M&A transactions. The treatment variable is $Target\_Software$ in column A, while it is $Target\_Tech$ in column B. The outcome variable in the present study is the predicted $Opacity\_Absolute$. In the propensity score estimation, changes in the standard deviation of each variable before and after matching are visually depicted in the accompanying figures (Graphs 3.1 to 3.3). It is evident that the post-matching standard deviation of most variables has decreased. Even the standard deviation of $Size$ and $Deposi\ growth$ has not decreased in some graphs, data balance tests provided at the top of each table fail to reject the hypothesis of no systematic differences between the treatment and control groups. We also present observations that are on-support and off-support. Notably, there are only a limited number of 5 observations in the off-support category.

In Table 3.5, we employed kernel matching to predict the matching score estimators. The ATT of $Target\_Software$ is -0.415 at a significance level of 5%, while the ATT of $Target\_Tech$ is -0.362 at a significance level of 5%. Shifting to caliper matching in Table 3.6 resulted in similar ATTs of $Target\_Software$ (-0.495, significant at the 5% level) and $Target\_Tech$ (-0.358, but not significant), with the ATT of $Target\_Tech$ loses significance. Moving to the nearest-neighbor matching within caliper, as shown in Table 3.7, maintains a significantly negative ATT of $Target\_Software$ (-0.438, significant at 10% level), while the ATT of $Target\_Tech$ remains negative but fails to reach statistical significance.

The robustness test using an alternative opacity measure ($Opacity\_Negative$) is presented in Table 3.8. For the sake of brevity, data balance tests are not presented. T-tests across all examinations fail to reject the hypothesis of any systematic differences between the treatment and control groups. The treatments variable are $Target\_Software$ in column A and $Target\_Tech$ in column B. Propensity scores are estimated using logistic regression, and the matching score estimators are performed using kernel matching in Panel A, caliper matching in Panel B, one-to-four nearest-neighbor matching within caliper in Panel C. The robustness test using $Opacity\_Negative$ yields result consistent with those obtained from $Opacity\_Absolute$. $Target\_Software$ is significantly negatively predicts $Opacity\_Negative$. $Target\_Tech$ shows a negative correlation with $Opacity\_Negative$ whereas this correlation is not statistically significant when employing caliper matching and nearest-neighbor matching within caliper. The mitigating impact of M&As appears more pronounced for $Target\_Software$ compared to $Target\_Tech$ due to the inclusion of 3 additional technology-driven M&A transactions in the $Target\_Tech$ category. These additional technology-driven M&A transactions do not belong to software and information sector, resulting potential bias when using $Target\_Tech$ as the treatment variable. In summary, our PSM analysis suggests that technology-driven M&A transactions are negatively associated with bank opacity.

3.4.2 DID-PSM analysis

As previously mentioned, adhering to the assumption to ignorability in PSM analysis necessitates a comprehensive set of covariates. To account for endogeneity stemming from unobservable variables that remain constant over time, we adopted the DID-PSM approach (Heckman et al, 1997), using a panel dataset that consists of samples one year prior and after each M&A event. This matching process yielded a dataset comprising 459 observations before treatment and 381 after treatment. We utilize kernel matching with the default Epanechnikov kernel function to match the treated and control groups and estimate the ATT on the treated.

Table 3.9 presents the ATT estimated via the DID-PSM approach. The outcome variable is $Opacity\_Absolute$, and the treatment variable is

$Target\_Software$ in both column A and B. We also conducted estimations using $Target\_Tech$ and $Opacity\_Negative$, yielding similar results to the presented results. In column A, we initially employ the same variables as in the PSM analysis to estimate propensity scores, subsequently incorporating additional variables such as $M\&A\_Sum$, $Foreign\_M\&A\_Sum$, $Prior\_M\&A\_Sum$, *and* $Prior\_Foreign\_M\&A\_Sum$ in column B to further control for the influence of M&A frequency. The estimated Pseudo R-squared increases from 0.134 to 0.169, suggesting the explanatory power of these factors. The ATT is negative in both column A (-0.374, but not significant at the 10% level) and significantly negative in column B (-0.401, significant at the 10% level). Taken together, our results remain consistent even after addressing the potential endogeneity arising from immutable unobservable variables.

3.4.3 Effects of foreign technology-driven M&As

We extend our analysis to assess the ATT for foreign technology-driven M&A, specifically by examining the interaction term between $MA\_Foreign$ and $Target\_Software$. Table 3.10 presents the ATT of foreign M&A and foreign technology-driven M&A transactions on opacity. Panel A utilizes $Target\_Foreign$ as the treatment variable, while Panel B employs $Target\_Foreign\_Soft$. The outcome variable is the predicted $Opacity\_Absolute$. In comparison to column A, variables to indicate M&A frequency are additionally incorporated into propensity score estimation in column B. We also conducted estimations using $Opacity\_Negative$, and $Target\_Foreign\_Tech$, employing both PSM and DID-PSM analysis. The results obtained are similar to those of $Target\_Foreign\_Soft$ and $Opacity\_Absolute$, which are omitted for the sake of brevity. We observed that bank opacity is not significantly influenced by foreign M&As. However, compared to the ATT of foreign M&As and technology-driven M&As, bank opacity is more significantly attenuated by foreign technology-driven M&A, with the ATT being -0.795, significant at the 1% level (Panel B). This could be attributed to improved technology integration with foreign tech firms or enhanced risk diversification, which is in line with McCarthy and Aalbers (2016)'s "assets of foreignness" hypothesis that cross-border M&As lead to increased patent applications, the infusion of insights stemming from cultural differences, and access to new markets.

3.5 Further analysis

In this section, we delve into the stock market's reaction to technology-driven M&As by examining the dynamics of stock price synchronicity, risk composition associated with such transactions. Stock price will be more informative when bank opacity is reduced. However, conflicting arguments have arisen regarding the relationship between stock price informativeness and synchronicity. Another additional consequence of changes in opacity is the alteration of risk composition. Increased transparency enhances the reliability of firm-specific information and refines the idiosyncratic component of risk.

Following Morck et al. (2016) and Abedifar et al. (2021), stock return synchronicity is measured as the logit transformation of the R-squared statistic from a regression of the individual stock return on market return as follows (formula 3.9). Here, $MarketR_t$ represents the day t market return which is indexed by Tokyo Stock Price Index ($TOPIX$), and $StockR_{it}$ is the daily stock return of bank i. The $TOPIX$ encompasses all stocks listed on the prime market division (First Section before April 4, 2022) of the Tokyo Stock Exchange and contain over 90% market cap of Japanese equities. The number of constituent securities is variable. $TOPIX$ is constructed using a market capitalization-weighting method, with the weighting is adjusted for float. Regressions for each bank are conducted on a quarterly basis from January 4, 1999 to June 30, 2022, with R-squared statistics (R^2) obtained from each estimation. Stock return synchronicity (SYN_{it}) for bank i during quarter t is computed by taking the natural logarithm of the ratio between the explained return variance (σ_m^2) and the unexplained return variance (σ_ε^2), as expressed in formula (3.10). By using $TOPIX$ as the market index in formula (3.9), the absolute value of the estimated betas (β_1) represent the quarterly systematic risk, which is the quarterly volatility of an individual stock concerning the overall market. The estimated idiosyncratic risks are calculated based on the bank-quarter volatility of error term in formula (3.9). They represent quarterly specific risk that is not related to overall market movements. $Nikkei$ 225 is also employed as a market index in the robustness test. Comprising 225 constituent securities, $Nikkei\,225$ represents large Japanese stocks and is constructed using a modified price-weightings method.

$$StockR_{it} = \alpha_0 + \beta_1 MarketR_t + \varepsilon_{it} \tag{3.9}$$

$$SYN_{it} = \ln\left[\frac{R_{it}^2}{1 - R_{it}^2}\right] = \ln\left[\frac{\sigma_m^2}{\sigma_\varepsilon^2}\right] = \ln(\sigma_m^2) - \ln(\sigma_\varepsilon^2) \tag{3.10}$$

Descriptive statistics are reported in Panel D and E of Table 3.4. We gathered a total of 335,535 daily stock returns, $TOPIX$ and $Nikkei\,225$ returns. Graph 3.4 depicts the time variations of mean stock return of Japanese commercial banks, $TOPIX$ return, and $Nikkei\,225$ return, with all expressed in percentages. The synchronicity between $TOPIX$ return and mean stock return, as well as between $Nikkei\,225$ and the mean stock return, is observed to be lower. To ensure data quality, we narrowed down our sample to include stock returns with a minimum of 3 observations per quarter for each bank. We conducted regression analysis (formula 3.9) and predicted 5,941 observations for synchronicity, resulting in 1,368 retained observations after merging with the financial dataset. The average SYN_TOPIX is -0.425 and the average SYN_Nikkei is -0.840. A higher SYN value indicates a greater degree of co-movement between a stock and the market index. Therefore, the predicted SYN aligns with the findings from Graph 3.4. The mean values of predicted SYN, $Beta$, and $Idiosyncratic$ are illustrated in Graph 3.5 and Graph 3.6, showcasing a consistent trend regardless of the market index employed.

Table 3.11 and 3.12 present the estimated results regarding the relationship between technology-driven M&A and both stock price synchronicity and risk composition. The treatment variable is $Target\_Software$, and the outcome variable is the predicted SYN, $Beta$, and $Idiosyncratic$. Outcome variables in Table 3.11 are predicted with $TOPIX$, while they are predicted with $Nikkei\,225$ in Table 3.12. Propensity scores are estimated using logistic regression. We used different variables to estimate propensity scores, such as including $M\&A\_Sum$,

$Foreign\_M\&A\_Sum$, $Prior\_M\&A\_Sum$, $Prior\_Foreign\_M\&A\_Sum$ and other bank financial variables. Matching score estimators are performed using DID-PSM with kernel matching. The ATT is significantly negative for SYN and $Beta$ in both table 3.11 and Table 3.12, indicating that the technology-driven M&As negatively predict stock price synchronicity and systematic risk. There is no notable impact on the idiosyncratic risk, regardless of the market index employed. We also conducted estimations using $Target\_Tech$, which yields similar results to $Target\_Software$. For the sake of brevity, the robustness test using different variable are omitted. Our outcome aligns with the findings of Jones et al. (2012), who concluded that bank investments in opaque assets can increase systematic risk while reducing idiosyncratic risk. Opacity in financial markets can erode their information efficiency, leading to increased price synchronicity and a heightened susceptibility to systemic market failure triggered by the risk perceptions of external investors (Jones et al., 2012). Our analysis provides evidence that banks' involvement in technology-driven M&As may reduce opacity, leading to decreased stock price synchronicity and lower vulnerability to systemic market failure.

3.6 Conclusions and limitations

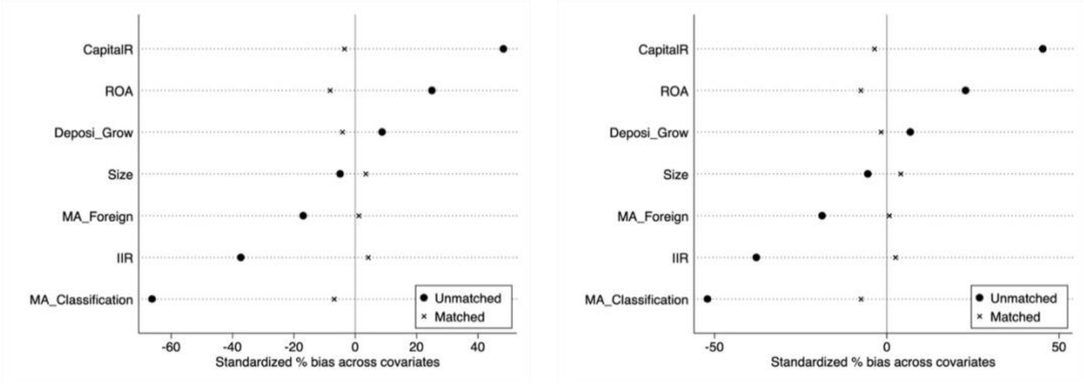
The present study investigates whether banks' engagement in technology impacts their opacity, a characteristic in banking industry known to impede market efficiency. This research question is explored by evaluating the effects of technology-driven M&As. We employ both propensity score matching (PSM) and differences-in-differences PSM (DID-PSM) to assess the average treatment effects on the treatment group. Our findings provided evidence that technology-driven M&A transactions are negatively associated with bank opacity. This result remains robust across various econometric techniques and different outcome variables. Moreover, we also observed that the attenuation effect is more pronounced of foreign technology-driven M&As.

Additionally, we further investigate how stock price synchronicity and risk composition are affected following technology-driven M&A transactions, as bank opacity is inversely related to stock price informativeness. Our analysis showed that banks' involvement in technology-driven M&As also leads to reduced stock price synchronicity and systematic risk. In accordance with Jones et al. (2012), opacity in financial markets can erode their information efficiency, leading to heightened price synchronicity and increased susceptibility to systemic market failure. Consequently, we concluded that technology-driven M&As potentially lower the vulnerability to systemic market failure and contribute to stock market stability.

However, our research has some limitations. First, the influencing mechanisms by which technology-driven M&As reduce bank opacity are ambiguous. We hypothesized that there may be channels of knowledge synergy and risk diversification, but further research is necessary to explore these aspects. Second, we only utilized the absolute residuals of loan loss provisions to measure bank opacity, including $Opacity\_Absolute$ and $Opacity\_Negative$. Alternative measure such as bond splits and kappa statistics (Morgan, 2002) should also be tested if the data is available. Third, while technology-driven M&As reduce the vulnerability to systemic market failure, we must acknowledge the technology-trigged riskiness, given the inherently riskiness of high-tech industry and the increasingly close relationship between incumbent banks and technology companies. Last, our research question is exclusively examined within a Japanese context, and the finding may not necessarily align with other countries due to different market and industry traits. Further analysis, including different measures, national factors, and technology industry-specific factors should be explored.

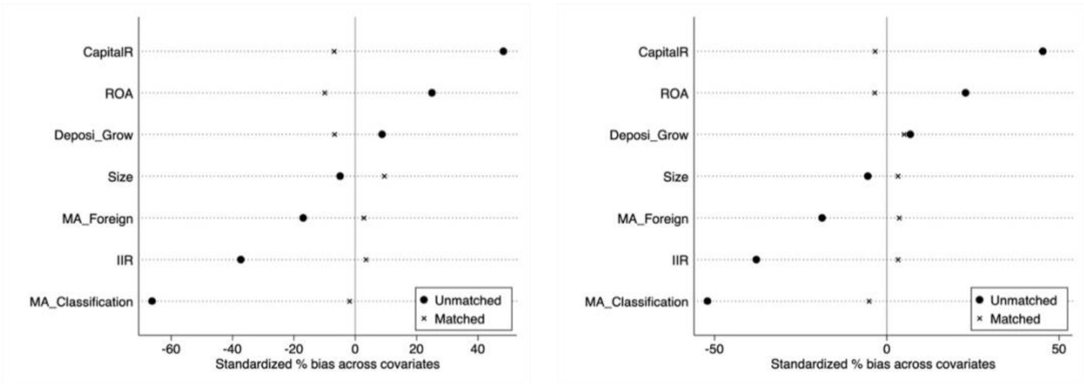
Graphs and Tables

The graphs and tables discussed in the present study are displayed here.



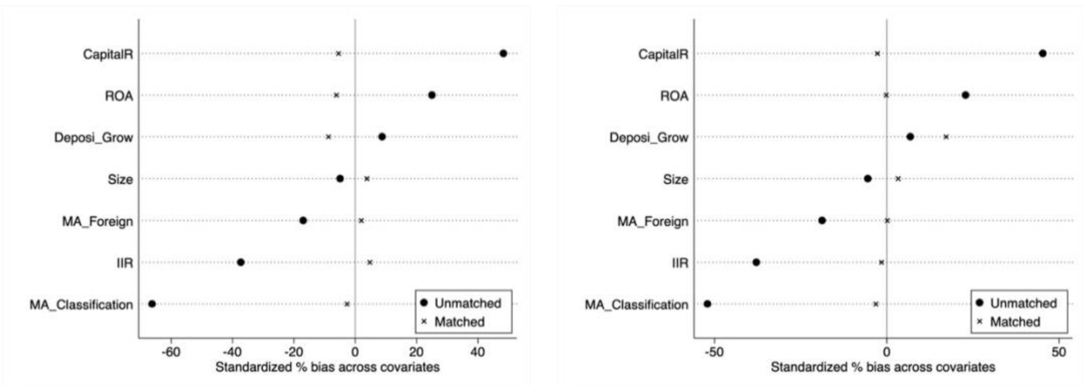
(a) (b)

Graph 3.1. Data balance test within kernel matching analysis



(a) (b)

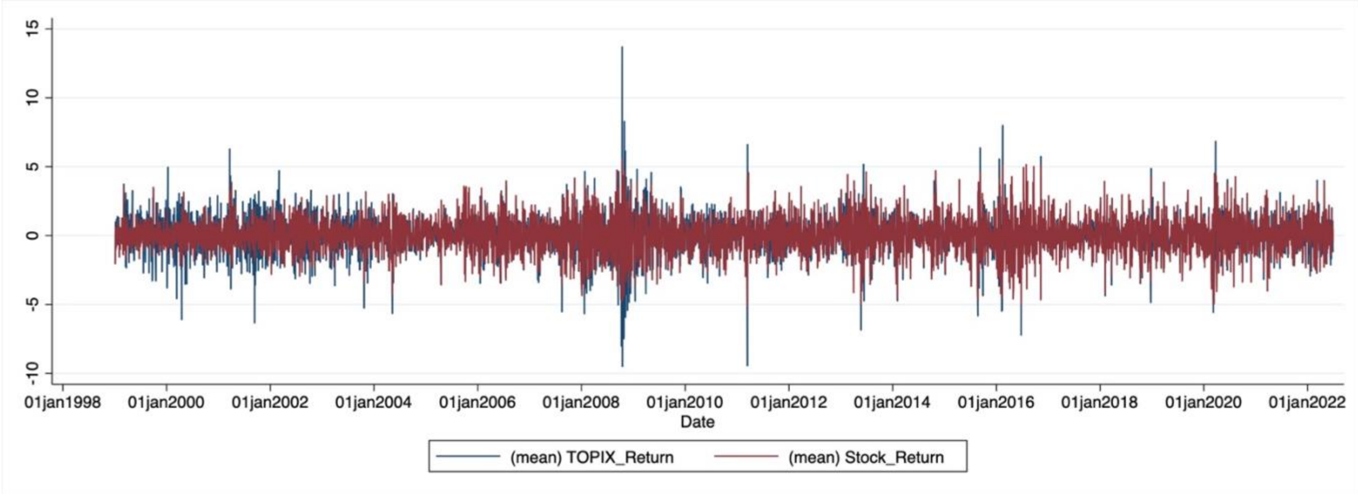
Graph 3.2. Data balance test within caliper matching analysis



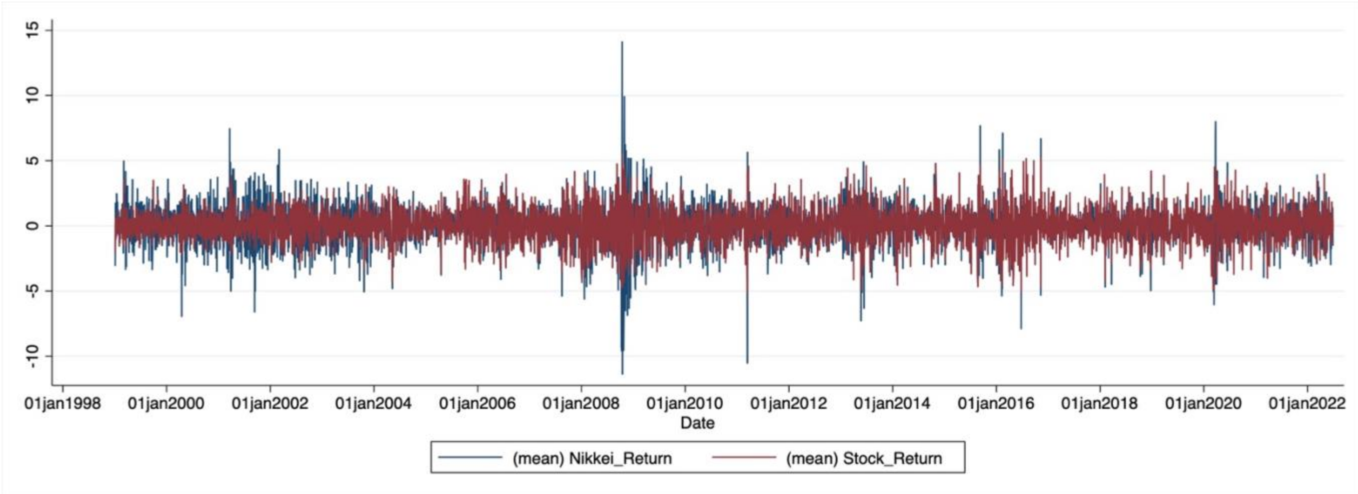
(a) (b)

Graph 3.3. Data balance test in nearest-neighbor matching within caliper analysis

Notes: Graphs 3.1 to 3.3 depict the data balance tests corresponding to the estimation results presented in Table 3.5 to 3.7. In these graphs, the outcome variable is the predicted $Opacity\_Absolute$*. The treatment variable is* $Target\_Software$ *in subfigure (a), while it is* $Target\_Tech$ *in subfigure (b).*



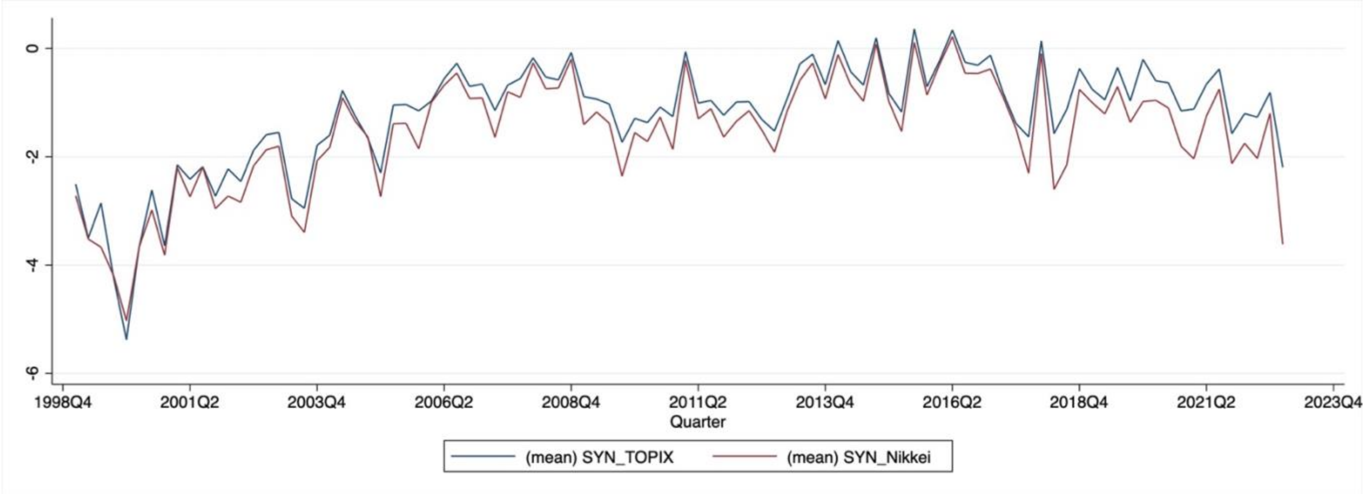
(a)



(b)

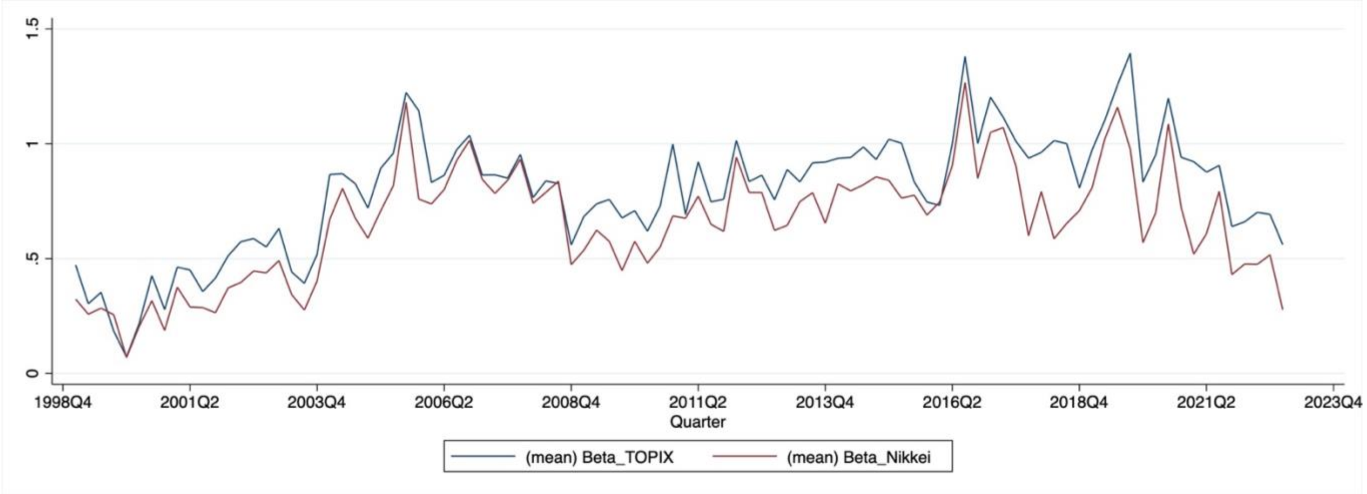
Graph 3.4. Time variations of series data

Notes: Graph 3.4 depicts the time variations of TOPIX return and mean stock return of Japanese commercial banks in subfigure (a), as well as the time variations of Nikkei return and mean stock return of Japanese commercial banks in subfigure (b). All expressed in percentages.

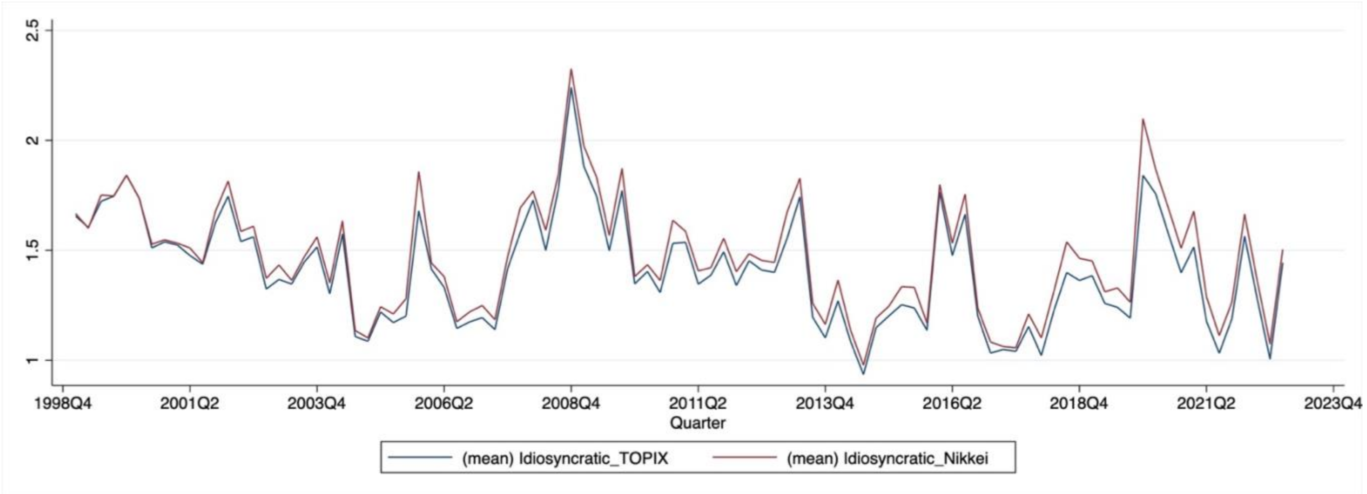


Graph 3.5. Time variation of predicted synchronicity

Notes: Graph 3.5 depicts the time variation of predicted synchronicity (SYN_TOPIX *and* SYN_Nikkei*), using different index (TOPIX and Nikkei225) as market index. The* SYN *for banks in each quarter are summarized and presented as their mean value.*



(a)



(b)

Graph 3.6. Time variation of predicted *systematic and idiosyncratic risk*

Notes: Graph 3.6 depicts the time variation of predicted systematic risk (Beta_TOPIX and Beta_Nikkei) in subfigure (a), and the time variation of predicted idiosyncratic risk (Idiosyncratic_TOPIX and Idiosyncratic_Nikkei) using different index (TOPIX and Nikkei225) as market index. Beta and idiosyncratic risk for banks in each quarter are summarized and presented as their mean value.

Table 3.1 Industry distribution of M&A targets

Industry	1999~ 2000	2001~2005	2006~2010	2011~2015	2016~2020	2021~2022	Sum
1.Fishery, Agriculture, and Forestry	0	0	0	1	1	0	2
2.Mining	0	0	0	0	0	0	0
3.Construction	0	1	1	4	0	0	6
4.Foods	0	0	0	3	0	0	3
5.Textiles	0	2	0	0	0	0	2
6.Paper and Pulp	0	0	0	0	0	0	0
7.Chemicals	0	1	1	2	2	0	6
8.Pharmaceutical	0	0	0	2	0	0	2
9.Coal and Petroleum	0	0	0	0	0	0	0
10.Rubber Products	0	0	0	0	0	0	0
11.Publishing and Printing	0	1	0	0	0	0	1
12.Ceramics	0	1	0	1	1	0	3
13.Iron and Steel	0	0	1	0	0	0	1
14.Nonferrous Metals and Metal Products	0	0	0	1	1	0	2
15.Machinery	0	0	3	1	1	0	5
16.Electric Appliances	0	1	1	5	1	0	8
17.Transportation Equipment	0	0	0	1	2	0	3
18.Precision Instruments	0	1	0	2	0	0	3
19.Other Manufacturing	0	1	0	2	0	0	3
20.General Trading Company	0	0	0	0	0	0	0
21.Food Wholesale	0	0	1	0	0	0	1
22.Pharmaceutical Wholesale	0	0	0	0	0	0	0
23.Other Sales and Wholesale	0	1	0	0	1	0	2
24.Department Stores	0	1	0	0	0	0	1
25.Supermarkets and Convenience Stores	0	0	1	2	0	0	3
26.Electronics Retail Stores and Home Centers	0	0	1	1	0	0	2
27.Other Retail	0	0	0	1	1	0	2
28.Food Service	0	0	0	0	1	0	1
29.Banks	9	12	18	17	13	5	74
30.Shinkin and Shinkumi	2	6	0	1	0	0	9
31.Insurance	0	0	1	0	1	0	2
32.Securities	0	1	2	7	6	1	17
33.Other Financing Business	0	8	28	36	79	8	159
34.Transportation and Warehousing	0	0	2	2	1	0	5
35.Electricity and Gas	0	0	0	0	0	1	1
36.Telecommunications and Broadcasting	0	0	0	0	0	0	0
37.Real Estate and Hotels	0	4	4	3	2	2	15
38.Amusement and Entertainment	0	0	0	0	0	0	0
39.Software and Information	**0**	**1**	**9**	**5**	**36**	**11**	**62**
40.Services	0	3	6	11	31	4	55
Total	11	46	80	111	181	32	461

Notes: Table 3.1 presents the industry distribution of M&A targets. Data sourced from the Recof M&A database spans from 1996 to 2023.5, with M&A transactions categorized into 40 industries based on the 33-industry classification established by the Tokyo securities exchange. M&A transactions are matched with datasets from banking sector. 1165 observations have been collected, and 461 of them have been matched with bank financial data. The retained data covers the period from 1999.4 to 2022.3.

Table 3.2 Technology-driven M&A distribution across different bank types

Panel A: City banks	1999~2000	2001~2005	2006~2010	2011~2015	2016~2020	2021~2022	Sum
Technology-driven M&A ($Target\_Software$)	0	0	5	1	**8**	4	18 (11.76%)
Other M&A	0	18	41	37	30	9	135 (88.24%)
Sum	0	18	46	38	38	13	153 (100%)
Panel B: Regional banks							
Technology-driven M&A ($Target\_Software$)	0	1	3	1	**8**	3	17 (10.83%)
Other M&A	6	18	14	32	64	6	140 (89.17%)
Sum	6	19	17	34	72	9	157 (100%)
Panel C: Secondary regional banks							
Technology-driven M&A ($Target\_Software$)	0	0	1	1	**7**	2	11 (12.09%)
Other M&A	5	6	3	29	34	3	80 (87.91%)
Sum	5	6	4	30	41	5	91 (100%)
Panel D: New types of banks							
Technology-driven M&A ($Target\_Software$)	0	0	0	1	**13**	2	16 (26.67%)
Other M&A	0	3	13	8	17	3	44 (73.33%)
Sum	0	3	13	9	30	5	60 (100%)

Notes: Table 3.2 presents the distribution of retained M&A targets across various types of banks. Panel A showcases city banks as acquirers, Panel B features regional banks, Panel C highlights secondary regional banks, and Panel D focuses on emerging bank types like online banking. The data is sourced from the Recof M&A database, encompassing the period from 1999.4 to 2022.3.

Table 3.3 Technology-driven, and foreign M&A distribution

Panel A	1999~2000	2001~2005	2006~2010	2011~2015	2016~2020	2021~2022	Sum
Technology-driven M&A ($Target\_Tech$)	0	1	9	5	**39**	**11**	65
Other M&A	11	45	71	106	142	21	396
Sum	11	46	80	111	181	32	461
Panel B							
Foreign M&A	0	0	**15**	**24**	**18**	**10**	67
Domestic M&A	11	46	65	87	163	22	394
Sum	11	46	80	111	181	32	461

Notes: Table 3.3 presents the distribution of retained M&A targets. Data is sourced from the Recof M&A database, covering the period from 1999.4 to 2022.3. Technology-driven M&A refers to transactions involving a target that belong to software and information, or those where the M&A transcripts include discussions on "Financial technology, Payment, Cashless, Information technology, Technology, Big data, Innovation" as relevant topics. This definition excludes discussion on technology specifically related to environmental protection technology. Foreign M&A refers to transaction involving Japanese acquirers and foreign targets.

Table 3.4 Descriptive statistics

Variable	Obs	Mean	Std. dev.	Min	Max
Panel A: M&A variables					
(Cross-sectional data, 2000 ~ 2022.3)					
Target_Software	461	0.134	0.342	0	1
Target_Tech	461	0.141	0.348	0	1
M&A_Foreign	461	0.145	0.353	0	1
M&A_Classify	461	1.293	0.635	1	5
Sum_M&A	461	3.087	2.451	1	10
Sum_Foreign_M&A	461	0.629	1.179	0	6
Panel B: Predict opacity measures					
(Panel data, 1999 ~ 2023)					
Loans Loss Provision	1362	50044.330	119035.700	77.000	1035468.000
Loans	1362	62.806	9.769	7.025	77.126
NPLR	1362	3.964	2.620	0.131	13.928
Opacity_ Absolute	1362	3.137	4.490	0.000	25.537
Opacity_Negative	1362	2.880	4.472	0.000	25.537
Panel C: Bank variables					
(Panel data, 3-year period that includes M&A event year, 1 year before and 1 year after M&A event)					
Size	1301	16.359	1.631	12.900	19.081
Deposit growth	1301	3.918	5.329	-5.724	26.220
Capital	1301	5.670	2.227	2.645	17.585
IIR	1301	53.589	14.602	2.403	87.686
ROA	1301	0.506	0.506	0.057	0.535
Panel D: Predict stock price synchronicity					
(Panel data, 2000.01.04 ~ 2022.12.30)					
Stock return	335535	0.004	1.853	-5.339	5.818
TOPIX return	335535	0.015	1.317	-9.523	13.729
Nikkei return	335535	0.022	1.440	-11.406	14.150
Quarter group	5941	56.964	29.505	1	96
Panel E: Stock market variables					
(Panel data, 3-quarter period that includes M&A event quarter, 1 quarter before and 1 quarter after M&A event)					
SYN_TOPIX	1368	-0.425	1.212	-11.295	1.687
Beta_TOPIX	1368	1.033	0.366	-0.517	2.316
Idiosyncratic_TOPIX	1368	1.368	0.465	0	3.321
SYN_Nikkei	1368	-0.840	1.341	-12.645	1.351
Beta_Nikkei	1368	0.849	0.352	-0.556	1.768
Idiosyncratic_Nikkei	1368	1.463	0.482	0	3.417

Notes: Table 3.4 summarizes the descriptive statistics for all variables. M&A transaction data (1999.04 ~ 2022.03) is collected from Recof M&A database, while banking financial data (1999~2023) and Japanese stock market data (1999.01.04~2022.06.30) are obtained from NEEDS FinancialQUEST. The top and bottom 1% of the banking data are winsorized.

Table 3.5 ATT on opacity within kernel matching analysis

	Column A				Column B			
Propensity score estimation	Logistic regression				Logistic regression			
Variable	Treated	Control	% bias	Pr > |t|	Treated	Control	% bias	Pr > |t|
Size	16.489	16.433	3.4	0.847	16.469	16.403	4.0	0.817
Deposit growth	4.407	4.644	-4.2	0.840	4.302	4.397	-1.7	0.932
Capital	5.998	6.103	-3.5	0.799	5.935	6.042	-3.6	0.789
IIR	52.147	51.461	4.2	0.789	51.975	51.573	2.5	0.869
ROA	0.456	0.515	-8.2	0.483	0.449	0.503	-7.6	0.502
MA_Foreign	0.105	0.102	1.1	0.948	0.100	0.098	0.7	0.968
MA_Classify	1.018	1.051	-6.9	0.416	1.067	1.106	-7.5	0.545
Number of obs.	461				461			
Pseudo R2	0.137				0.106			
Matching score analysis	Kernel matching				Kernel matching			
Outcome variable	Opacity_Absolute				Opacity_Absolute			
Treatment variable	Target_Software				Target_Tech			
	Treated	Control	Difference	Pr > |t|	Treated	Control	Difference	Pr > |t|
ATT	**0.670**	**1 . 085**	**-0.415****	**0.024**	**0.711**	**1.074**	**-0.362****	**0.049**
	Treated	Control	Sum		Treated	Control	Sum	
On support	57	399	456		60	396	456	
Off support	5	0	5		5	0	5	
Total	62	399	461		65	396	461	

Notes: Table 3.5 presents the ATT of technology-driven M&A transaction. The treatment variable is Target_Software in column A, while the treatment variable is Target_Tech in column B. The outcome variable in the present study is the predicted Opacity_Absolute. Data balance tests on the mean value of each variable are provided at the top of each table. All t-tests fail to reject the hypothesis of no differences between the treatment and control groups. Propensity scores are estimated using logistic regression, and the matching score estimators are performed using kernel matching.

Table 3.6 ATT on opacity within caliper matching analysis

	Column A				Column B			
Propensity score estimation	Logistic regression				Logistic regression			
Variable	Treated	Control	% bias	Pr > |t|	Treated	Control	% bias	Pr > |t|
Size	16.489	16.335	9.5	0.591	16.469	16.416	3.2	0.851
Deposit growth	4.407	4.790	-6.8	0.756	4.302	4.023	5.0	0.792
Capital	5.998	6.205	-6.9	0.620	5.935	6.036	3.2	0.830
IIR	52.147	51.579	3.5	0.827	51.975	51.454	2.5	0.869
ROA	0.456	0.527	-10.0	0.405	0.449	0.474	-3.5	0.733
MA_Foreign	0.105	0.096	2.8	0.873	0.100	0.088	3.6	0.828
MA_Classify	1.018	1.027	-1.9	0.748	1.067	1.094	-5.2	0.657
Number of obs.	461				461			
Pseudo R2	0.137				0.106			
Matching score analysis	Caliper matching				Caliper matching			
Outcome variable	Opacity_Absolute				Opacity_Absolute			
Treatment variable	Target_Software				Target_Tech			
	Treated	Control	Difference	Pr > |t|	Treated	Control	Difference	Pr > |t|
ATT	**0.670**	**1.165**	**-0.495****	**0.015**	**0.711**	**1.069**	**-0.358**	**0.108**
	Treated	Control	Sum		Treated	Control	Sum	
On support	57	399	456		60	396	456	
Off support	5	0	5		5	0	5	
Total	62	399	461		65	396	461	

Notes: Table 3.6 presents the ATT of technology-driven M&A transaction. The treatment variable is Target_Software in column A, while the treatment variable is Target_Tech in column B. The outcome variable in the present study is the predicted Opacity_Absolute. Data balance tests on the mean value of each variable are provided at the top of each table. All t-tests fail to reject the hypothesis of no systematic differences between the treatment and control groups. Propensity scores are estimated using logistic regression, and the matching score estimators are performed using caliper matching.

Table 3.7 ATT on opacity in nearest-neighbor matching within caliper analysis

	Column A				Column B			
Propensity score estimation	Logistic regression				Logistic regression			
Variable	Treated	Control	% bias	Pr > |t|	Treated	Control	% bias	Pr > |t|
Size	16.489	16.427	3.8	0.832	16.469	16.416	3.3	0.851
Deposit growth	4.407	4.902	-8.8	0.685	4.302	3.339	17.2	0.320
Capital	5.998	6.161	-5.5	0.694	5.935	6.017	-2.8	0.826
IIR	52.147	51.378	4.7	0.766	51.975	52.231	-1.6	0.914
ROA	0.456	0.500	-6.2	0.578	0.449	0.450	-0.2	0.983
MA_Foreign	0.105	0.099	1.9	0.911	0.100	0.100	0.1	0.996
MA_Classify	1.018	1.031	-2.7	0.651	1.067	1.083	-3.2	0.769
Number of obs.	461				461			
Pseudo R2	0.137				0.106			
Matching score analysis	Nearest-neighbor matching within caliper				Nearest-neighbor matching within caliper			
Outcome variable	Opacity_Absolute				Opacity_Absolute			
Treatment variable	Target_Software				Target_Tech			
	Treated	Control	Difference	Pr > |t|	Treated	Control	Difference	Pr > |t|
ATT	**0.670**	**1.108**	**-0.438***	**0.069**	**0.711**	**1.043**	**-0.332**	**0.198**
	Treated	Control	Sum		Treated	Control	Sum	
On support	57	399	456		60	396	456	
Off support	5	0	5		5	0	5	
Total	62	399	461		65	396	461	

Notes: Table 3.7 presents the ATT of technology-driven M&A transaction. The treatment variable is Target_Software in column A, while it is Target_Tech in column B. The outcome variable in the present study is the predicted Opacity_Absolute. Data balance tests on the mean value of each variable are provided at the top of each table. All t-tests fail to reject the hypothesis of no systematic differences between the treatment and control groups. Propensity scores are estimated using logistic regression, and the matching score estimators are performed using nearest-neighbor matching within caliper. One-to-four matching is employed in this study.

Table 3.8 ATT on alternative opacity measure (*Opacity_Negative*)

Panel A:	Column A				Column B			
Matching score analysis	Kernel matching				Kernel matching			
Outcome variable	Opacity_Negative				Opacity_Negative			
Treatment variable	Target_Software				Target_Tech			
	Treated	Control	Difference	Pr > |t|	Treated	Control	Difference	Pr > |t|
ATT	**0.225**	**0.533**	**-0.308****	**0.041**	**0.284**	**0.546**	**-0.262***	**0.097**
Panel B:								
Matching score analysis	Caliper matching				Caliper matching			
Outcome variable	Opacity_Negative				Opacity_Negative			
Treatment variable	Target_Software				Target_Tech			
	Treated	Control	Difference	Pr > |t|	Treated	Control	Difference	Pr > |t|
ATT	**0.225**	**0.609**	**-0.384****	**0.028**	**0.284**	**0.589**	**-0.305**	**0.137**
Panel C:								
Matching score analysis	Nearest-neighbor matching within caliper				Nearest-neighbor matching within caliper			
Outcome variable	Opacity_Negative				Opacity_Negative			
Treatment variable	Target_Software				Target_Tech			
	Treated	Control	Difference	Pr > |t|	Treated	Control	Difference	Pr > |t|
ATT	**0.225**	**0.591**	**-0.366***	**0.079**	**0.283**	**0.615**	**-0.331**	**0.181**
	Treated	Control	Sum		Treated	Control	Sum	
On support	57	399	456		60	396	456	
Off support	5	0	5		5	0	5	
Total	62	399	461		65	396	461	

Notes: Table 3.8 presents the ATT of technology-driven M&A transaction on alternative opacity measure. The outcome variable in the present study is the predicted $Opacity\_Negative$. *The treatment variable is* $Target\_Software$ *and* $Target\_Tech$. *For the sake of brevity, data balance tests are not presented. All t-tests fail to reject the hypothesis of no systematic differences between the treatment and control groups. Propensity scores are estimated using logistic regression, and the matching score estimators are performed using kernel matching in Panel A, caliper matching in Panel B, one-to-four nearest-neighbor matching within caliper in Panel C.*

Table 3.9 ATT on opacity within DID-PSM estimation

	Column A					Column B				
Matching score analysis	Kernel matching					Kernel matching				
Outcome variable	Opacity_Absolute					Opacity_Absolute				
Treatment variable	Target_Software					Target_Software				
Pseudo R2	0.134					0.169				
	Treated	Control	Difference	S.Err.	Pr >|t|	Treated	Control	Difference	S.Err.	Pr >|t|
Before treatment	1.285	0.895	0.391	0.152	0.010	1.285	0.893	0.393	0.158	0.013
After treatment	0.891	0.874	0.016	0.178	0.927	0.891	0.899	-0.009	0.184	0.963
Diff - in - Diff			**-0.374**	**0.234**	**0.110**			**-0.401***	**0.242**	**0.098**
	Treated	Control	Sum			Treated	Control	Sum		
Before treatment	72	387	459			72	368	440		
After treatment	44	337	381			44	326	370		
Total	116	724	840			116	694	810		

Notes: Table 3.9 presents the ATT of technology-driven M&A transaction. The treatment variable is Target_Software, and the outcome variable is the predicted Opacity_Absolute. Compared to column A, variables such as M&A_Sum, Foreign_M&A_Sum, Prior_M&A_Sum, and Prior_Foreign_M&A_Sum to indicate M&A frequency are additionally incorporated into propensity score estimation in column B. We also conducted estimations using Target_Tech and Opacity_Negative, which yields similarly negative results to Target_Software. Propensity scores are estimated using logistic regression, and the matching score estimators are performed using DID-PSM with kernel matching.

Table 3.10 ATT of foreign M&As and foreign technology-driven M&As on opacity within DID-PSM estimation

Panel A	Column A					Column B				
Matching score analysis	Kernel matching					Kernel matching				
Outcome variable	Opacity_Absolute					Opacity_Absolute				
Treatment variable	Target_Foreign					Target_ Foreign				
	Treated	Control	Difference	S.Err.	Pr >|t|	Treated	Control	Difference	S.Err.	Pr >|t|
Before treatment	0.830	0.819	0.011	0.149	0.940	0.830	0.928	-0.098	0.246	0.690
After treatment	0.784	0.679	0.105	0.168	0.532	0.784	0.813	-0.030	0.290	0.918
Diff - in - Diff			**0.094**	**0.224**	**0.676**			**0.068**	**0.380**	**0.857**
	Treated	Control	Sum			Treated	Control	Sum		
Before treatment	73	257	330			73	88	161		
After treatment	59	214	273			59	66	125		
Total	132	471	603			132	154	286		
Panel B										
Matching score analysis	Kernel matching					Kernel matching				
Outcome variable	Opacity_Absolute					Opacity_Absolute				
Treatment variable	Target_Foreign_Soft					Target_Foreign_Soft				
	Treated	Control	Difference	S.Err.	Pr >|t|	Treated	Control	Difference	S.Err.	Pr >|t|
Before treatment	1.155	0.823	0.332	0.154	0.032	0.155	0.918	0.238	0.165	0.151
After treatment	0.269	0.732	-0.463	0.207	0.026	0.269	0.826	-0.557	0.250	0.026
Diff - in - Diff			**-0.795*****	**0.258**	**0.002**			**-0.795*****	**0.300**	**0.008**
	Treated	Control	Sum			Treated	Control	Sum		
Before treatment	7	355	362			7	339	346		
After treatment	3	294	297			3	286	289		
Total	10	649	659			10	625	635		

Notes: Table 3.10 presents the ATT of foreign M&A and foreign technology-driven M&A transactions on opacity. The treatment variable is Target_Foreign *in Panel A, and is* Target_Foreign_Soft *in Panel B. The outcome variable is the predicted* Opacity_Absolute*. Compared to column A, variables such as* M&A_Sum*,* Foreign_M&A_Sum*,* Prior_M&A_Sum*, and* Prior_Foreign_M&A_Sum *to indicate M&A frequency are additionally incorporated into propensity score estimation in column B. We also conducted estimations using* Opacity_Negative*, and* Target_Foreign_Tech*, employing both PSM and DID-PSM analysis. The results obtained are similar to those of* Target_Foreign_Soft *and are omitted for the sake of brevity. Propensity scores are estimated using logistic regression, and the matching score estimators are performed using DID-PSM with kernel matching.*

Table 3.11 ATT on stock price synchronicity, risk composition within DID-PSM estimation

Propensity score estimation			Logistic regression		
Matching score analysis			Kernel matching		
Treatment variable			Target_Software		
	Treated	Control	Difference	S.Err.	Pr >|t|
Panel A					
Outcome variable: SYN_TOPIX					
Before treatment	-0.395	-0.309	-0.085	0.103	0.410
After treatment	-0.710	-0.368	-0.343	0.104	0.001
Diff - in - Diff			**-0.257***	**0.146**	**0.079**
Panel B					
Outcome variable: Beta_TOPIX					
Before treatment	1.041	1.046	-0.005	0.033	0.880
After treatment	0.932	1.046	-0.114	0.033	0.001
Diff - in - Diff			**-0.109****	**0.047**	**0.021**
Panel C					
Outcome variable: Idiosyncratic_TOPIX					
Before treatment	1.284	1.381	-0.097	0.039	0.013
After treatment	1.296	1.357	-0.061	0.039	0.121
Diff - in - Diff			**0.036**	**0.056**	**0.514**
Before treatment	109	353			
After treatment	107	352			
Total	216	705			

Notes: Table 3.11 presents the ATT on stock price synchronicity, risk composition *of technology-driven M&A transaction. The treatment variable is $Target\_Software$. The outcome variable in the present study is SYN_TOPIX in Panel A, $Beta\_TOPIX$ in Panel B, $Idisyncratic\_TOPIX$ in Panel C. Propensity scores are estimated using logistic regression. We used different variables to estimate propensity scores, such as including $M\&A\_Sum$, $Foreign\_M\&A\_Sum$, $Prior\_M\&A\_Sum$, and $Prior\_Foreign\_M\&A\_Sum$ to indicate M&A frequency. The matching score estimators are performed using DID-PSM with kernel matching. We also conducted estimations using $Target\_Tech$, which yields similar results to $Target\_Software$. For the sake of brevity, the robustness test using different variable are omitted.*

Table 3.12 ATT on stock price synchronicity, risk composition within DID-PSM estimation

Propensity score estimation			Logistic regression		
Matching score analysis			Kernel matching		
Treatment variable			Target_Software		
	Treated	Control	Difference	S.Err.	Pr >|t|
Panel A					
Outcome variable: SYN_Nikkei					
Before treatment	-0.915	-0.701	-0.214	0.132	0.105
After treatment	-0.386	-0.784	-0.602	0.133	0.000
Diff - in - Diff			**-0.388****	**0.187**	**0.039**
Panel B					
Outcome variable: Beta_Nikkei					
Before treatment	0.814	0.876	-0.062	0.032	0.054
After treatment	0.696	0.865	-0.169	0.032	0.000
Diff - in - Diff			**-0.107****	**0.046**	**0.019**
Panel C					
Outcome variable: Idiosyncratic_Nikkei					
Before treatment	1.384	1.469	-0.085	0.041	0.040
After treatment	1.397	1.453	-0.055	0.041	0.183
Diff - in - Diff			**0.030**	**0.056**	**0.514**
Before treatment	109	353			
After treatment	107	352			
Total	216	705			

Notes: Table 3.12 presents the ATT on stock price synchronicity, risk composition *of technology-driven M&A transaction. The treatment variable is $Target\_Software$. The outcome variable in the present study is SYN_Nikkei in Panel A, $Beta\_Nikkei$ in Panel B, $Idisyncratic\_Nikkei$ in Panel C. Propensity scores are estimated using logistic regression. We used different variables to estimate propensity scores, such as including $M\&A\_Sum$, $Foreign\_M\&A\_Sum$, $Prior\_M\&A\_Sum$, and $Prior\_Foreign\_M\&A\_Sum$ to indicate M&A frequency. The matching score estimators are performed using DID-PSM with kernel matching. We also conducted estimations using $Target\_Tech$, which yields similar results to $Target\_Software$. For the sake of brevity, the robustness test using different variable are omitted.*

Appendix 3.1

Table A3.1 Variable definition

Panel A: M&A variables	
Acquirer	An acquirer is the acquiring party in an acquisition, or the buyer in a business transfer, capital participation, and capital expansion. In the case of a business transfer that results in the integration of existing operations, the merger is the entity with a higher market share.
Acquirer industry	The present study focuses on mergers involving listed commercial banks, or entities whose parent companies are listed commercial banks, as well as financial holding groups.
Target	The counterpart of the M&A transaction.
Target industry	There are 40 industry classifications (as shown in Table 1) in the Recof M&A database, which are derived from the Tokyo Stock Exchange's 33 industry classifications.
Target industry - software ($Target\_Software$)	This is a dummy variable that is 1 when the target industry is software and information, and 0 otherwise.
Target industry - technology orientated ($Target\_Tech$)	Technology-oriented M&A refers to transactions involving a target that belong to software and information, or those where the M&A transcripts include discussions on "Financial technology, Payment, Cashless, Information technology, Technology, Big data, Innovation" as relevant topics. This definition excludes discussion on "technology" specifically related to environmental protection technology.
Foreign M&A ($M\&A\_Foreign$)	This dummy variable takes a value of 1 for M&A transaction involving Japanese acquirers and foreign targets, and 0 for M&A transaction between Japanese companies.
M&A classification ($M\&A\_Classify$)	A dummy variable that categorizes M&A and M&A related transaction. It is equal to 1 for M&A, 2 for intra-group M&A, 3 for subsidiary acquisition (100% acquisition, subsidiary share repurchase), 4 for spin-off and division, and 5 for holding company.
M&A frequency ($Sum\_M\&A$)	The frequency of M&A transaction during a single timeframe which corresponds to a one-year or one-quarter period within our panel data analysis.
Foreign M&A frequency ($Sum\_Foreign\_M\&A$)	The frequency of foreign M&A transaction during a single timeframe which corresponds to a one-year or one-quarter period within our panel data analysis.
Prior M&A frequency ($Sum\_Prior\_M\&A$)	The frequency of M&A transaction during the prior timeframe corresponding to one year or one quarter before a specific M&A transaction within our panel data analysis.
Prior foreign M&A frequency ($Sum\_Prior\_Foreign\_M\&A$)	The frequency of foreign M&A transaction during the prior timeframe corresponding to one year or one quarter before a specific M&A transaction within our panel data analysis.

(Continued on the next page)

Table A3.1 Continued

Panel B: Bank variables	
Loan loss provision residuals ($Opacity\_Absolute$ in %)	The absolute value of the residuals in the regression model of loan loss provision (formulas 1 and 2).
Loan loss provision residuals ($Opacity\_Negative$ in %)	In the regression model of loan loss provision (formulas 3 and 3'), take the absolute value of negative residuals and set positive residuals to 0.
Non-performing loan ratio ($NPLR$ in %)	The ratio of non-performing loans to total loans. A measure of doubtful loans.$NPLR = \frac{Special\ attention\ loans + Doubful\ laons + Bankrupt\ or\ de\ facto\ bankrupt\ loans}{Total\ loans} * 100$
Size ($Size$ in %)	The natural logarithm of total assets. $Size = \log(Total\ assets)$
Deposit growth ratio ($Deposit\ growth$ in %)	The growth rate of deposits. $Depo\_growth_{it} = \frac{Deposits_{it} - Deposits_{i,t-1}}{Deposits_{i,t-1}} * 100$
Capital ratio ($Capital$ in %)	Net assets are divided by total assets. $Capital = \frac{Net\ assets}{Total\ assets} * 100$
Interest income ratio (IIR in %)	The ratio of interest income to ordinary revenue. $IIR = \frac{Interest\ income}{Ordinary\ revenue} * 100$
Return to assets (ROA in %)	The ratio of profit before tax to total assets. A measure of banking profitability. $ROA = \frac{Profit\ before\ tax}{Total\ assets} * 100$
Loan loss provisions (LLP in million Japanese yen)	The amount of specific funds that a financial institution sets aside to cover potential future loan losses, the purpose of which is to reflect the cost of expected credit losses in the institution's financial statements.
Loans ratio ($Loans$ in %)	The ratio of total loans to total assets. $Loans = \frac{Total\ loans}{Total\ assets} * 100$

(Continued on the next page)

Table A3.1 Continued

Panel C: Stock market variables	
Stock price return ($StockR$ in %)	The daily return of close price of each bank' stock.
Tokyo Stock Price Index ($TOPIX$)	TOPIX is employed as a market index. It encompasses all stocks listed on the First Section of the Tokyo Stock Exchange and contain over 90% market cap of Japanese equities. The number of constituent securities is variable. TOPIX is constructed using a market capitalization-weighting method, with the weighting is adjusted for float.
SYN_TOPIX	This is a measurement of stock price quarterly synchronicity estimated using a market model and $TOPIX$ (formulas 9 and 10). It is calculated for each bank quarter in the sample.
$Beta\_TOPIX$	By using $TOPIX$ as the market index in formula 9, the estimated beta represents the quarterly systematic risk or the quarterly volatility of an individual stock in relation to the overall market.
$Idiosyncratic\_TOPIX$	By using $TOPIX$ as the market index in formula 9, the estimated idiosyncratic risk represents quarterly specific risk which is not related to overall market movements, or the quarterly volatility of error term for an individual stock.
Nikkei Stock Average ($Nikkei$ 225)	Nikkei 225 is also employed as a market index. It contains 225 constituent securities and represents large Japanese stocks. Nikkei 225 is constructed using a modified price- weightings method.
SYN_Nikkei	This is a measurement of stock price synchronicity estimated using a market model and $Nikkei$ 225 (formulas 9 and 10). It is calculated for each bank quarter in the sample.
$Beta\_Nikkei$	By using $Nikkei$ 225 as the market index in formula 9, the estimated beta represents the quarterly systematic risk or the quarterly volatility of an individual stock in relation to the overall market.
$Idiosyncratic\_Nikkei$	By using $Nikkei$ 225 as the market index in formula 9, the estimated idiosyncratic risk represents quarterly specific risk which is not related to overall market movements, or the quarterly volatility of error term for an individual stock.

Notes: Table A3.1 summarizes the definition of all variables. M&A transaction data (1999.4 ~ 2022.03) is collected from Recof M&A database, while banking financial data (1999~2023) and Japanese stock market data (1999.01.04~2022.06.30) are obtained from NEEDS FinancialQUEST.

4 The Impact of Intangible Assets on Bank Efficiency: Evidence from Multinational Analysis and a Meta-SFA Approach

4.1 Introduction

The acquisition of software and technological products through M&As and purchases provides a pathway to adopt digital transformations, with the acquired assets being recorded as intangible assets on the balance sheet. Intangible assets have been so long recognized as increasingly critical for corporate development and firm value (Lev, 2003; Lim et al., 2020). Despite this, only scant literature assesses the magnitude of the impact of intangible assets in the banking industry because of their opacity resulting from limited information from financial reports and other corporate statements. Intangibles are reported in various accounting methods (or unreported). Internally created intangibles including patents and in-processing R&D are expensed as incurred under IFRS and GAAP, except for the development costs that are capitalized under IFRS. Externally purchased identifiable technology, marketing, and customer-related intangibles such as patents and trademarks are recorded on the balance sheet under U.S. GAAP (cost model) and IFRS (cost model and revaluation model). The excess of fair value in a business acquisition is reported separately as goodwill which is related to customer loyalty, off-balance-sheet activities, and so on. Others are identifiable legal rights that are also recorded as intangibles on the balance sheet. Intangibles are growing crucial for commercial banks in a knowledge-driven economy. Thus, the present study investigates how a bank's identifiable intangible assets (hereafter intangibles) which mainly contain software after excluding goodwill, impact a bank's performance.

The technology-oriented intangibles, serving as intellectual capital, are expected to increase firm efficacy and efficiency, thereby gaining a competitive advantage (Ordóñez de Pablos, 2003). Motivated by this, the present study investigates the impact of intangibles on the bank's efficiency. In addition to this, we give a plausible explanation for their relationship and address the importance of a detailed accounting method for intangibles. To this end, we begin with the regression for measuring banks' efficiency through a stochastic meta-frontier analysis (hereafter meta-SFA, Battese et al., 2004; Huang et al., 2014; Lee et al., 2021). Banks' individual efficiency scores are predicated through the regression of individual banks' total costs to banks' inputs and outputs within a single-country setup, while the meta-efficiency scores are estimated by regressing predicated cost frontiers (excluding inefficiency terms from original costs) against inputs and outputs within a group of countries to measure the multinational efficiency gap. The estimated efficiency scores (individual efficiency and meta-efficiency) are regressed on the intangibles within a two-way fixed effects model. Our data focuses on the 624 commercial banks from 4 areas that consist of 30 countries, the European Union (EU, 27 countries), United States (US), Japan (JP), and Mainland China (CN), which provides a total sample of 5,277 observations over a 10-year period from 2012 to 2021.

There are unobservable omitted bias and endogeneity problems that challenge the relationship between intangibles and banks' efficiency. As banks possess more intangible assets, they can offer a wider range of financial products and services, leading to the economics of scale while enhancing their market power and competitiveness. By the quiet-life hypothesis (Berger & Hannan, 1998), banks' efficiency decreases as market power increases because larger banks are managed without cost minimization. Hence, the present study employs different competitiveness measures to account for this endogeneity concern. However, the ES hypothesis (Berger, 1995) argues that efficiency improves banking profitability and increases concentration. To mitigate the issue of reverse causality between efficiency and competitiveness, instrument variables are employed, and estimation is conducted using a 2-stage least square (2SLS) and the generalized method of moments (GMM).

Accuracy caveats of our analysis are in order. First, the presence of land use rights and trademarks among the intangible assets poses a challenge to our results and explanation. To assess a more accurate value of technology-related assets, we adopt the positive values of the residuals after regressing intangibles against total assets. This is because land use rights and trademarks may be correlated with a bank's size and total assets, whereas technological assets, especially new patents held by small and medium banks that struggle to survive through technological innovation, may not be strongly associated with their total assets. Another concern is that fintech industry compets with banking sector and compels incumbent banks to improve innovation and operating efficiency (Lee et al., 2021). Thus, simply regressing efficiency on the intangible assets may generate a spurious correlation problem. To further eliminate concerns that technology impacts bank efficiency via other mechanisms, we additionally control the Global Fintech Index. Finally, the impact on banks' total efficiency that is generated when regressing all samples together, is additionally examined.

The overarching results from our estimation are that intangibles enhance a bank's efficiency, and the fostering effects act more on the improvement of meta-efficiency. Intangibles also positively predict their individual efficiency, albeit not very conclusive and robust. The plausible explanation for our finding is the amelioration of macro-environmental restrictions. The integration of technology in the financial industry enables banks to mitigate information asymmetry and enhance the efficient allocation of input materials based on varying domestic demands, which increases banks' meta-efficiency. But the emphasis on intangibles is at the cost of cutting the bank's core business activities, resulting in reduced outputs and relatively unnoticeable individual efficiency alteration.

The improvement of meta-efficiency and the reduction of macro-environmental restrictions sparks our research interest in the impact on efficiency convergence because the removal of national restrictions is expected to foster perfect competition and expedite efficiency convergence. The interaction term of intangibles and lagged efficiency scores proves that intangibles positively predict efficiency convergence (negative coefficients of interaction terms). Moreover, the interaction term of the Global Fintech Index shows that the national fintech development level influences the competition and cooperation, which differentiates incumbent commercial banks and reduces meta-efficiency convergence.

Nevertheless, banks' response, such as procurement of technology-related products, tends to homogenize this differentiation, promote convergence, and enhance the perfect competition of markets.

Our analysis extends the extant literature on bank efficiency and literature on intangible assets, making contributions in the following ways. First, we provide empirical evidence supporting the positive correlation between recorded identifiable intangible assets and bank efficiency, offering a rational explanation for their relationship. The intangible assets are recognized as opaque assets, with most research focusing on their valuation, particularly for unrecorded intangibles. Our study reveals that intangibles assets, especially technology-related intangibles, has the potential to enhance bank efficiency, calling for comprehensive disclosure of these recorded intangible assets by both large and small banks, to strengthen external monitoring and assist investors in accurate evaluation.

Second, to document efficiency convergence and the impacts of the national fintech development level, we test our research question in a multinational context, which is an aspect rarely explored in previous research. This multinational perspective is crucial, as legislative deregulation improves the continuity of the international financial system, thereby enhancing cross-border trade, investment, and financial activities. Moreover, the integration of technology into the banking industry has facilitated monitoring and expanded international business, underscoring the pressing need for this research.

This chapter is organized into 6 sections. Section 4.2 introduces literature reviews related to factors that influence bank efficiency. Then we describe the methodology that consists of empirical models and variables in Section 4.3. Empirical results of baseline regression and robustness test are reported in Section 4.4, which is flowed by a further analysis on efficiency convergence in Section 4.5. Finally, we conclude and provide a further discussion in Section 4.6.

4.2 Literature review

There is a plethora of research on bank productivity and cost efficiency. Employing both the parametric method such as stochastic frontier analysis (SFA) and the non-parametric method such as data envelop analysis (DEA), previous research investigated how bank-specific factors and nation-specific factors impact bank efficiency. Recently, against the background that financial technology offers an array of services on a global stage and the trend that banks begin to cooperate with tech firms in ways of capital injection and credit line, the extent to which financial technology impacts bank efficiency has assembled academic attention. Thus, in this section, we first review the determinants of bank efficiency which is followed by a discussion on the impact of financial technology.

4.2.1 Bank-specific factors

Publicly listed (*Listed*): Initial public offering (IPO) is one of the ownership diversifying strategies that are expected to improve bank efficiency (Luo & Yao, 2010). Industrial opacity is ameliorated, and financial reports become more accurate after stock listing. Publicly traded banks must comply with the disciplines of the capital market, receive external monitoring, and are expected to achieve better efficiency then. Moreover, conditioning that banking industry is relatively more opaque than other firms (Morgan, 2002), external monitoring is significantly important for improving banking transparency and efficiency. To explore the effects of ownership diversification on bank efficiency, employing the intermediation approach of input-orientated DEA, Luo and Yao (2010) proved that bank efficiency increased by almost 5% after listing.

Non-performing loans (*NPLR*): One of the primary sources of bank inefficiency lies in the inefficiency of its deposit-producing sub-process (Xiaogang, Skully, & Brown, 2005; Wang et al., 2014). Over the reform period from 2004 to 2005 in China, state-owned commercial banks were better performing due to the reduction of over-employment and disposal of NPLs (Wang, Huang, Wu, & Liu, 2014; Yao, Han, & Feng, 2008), indicating the explaining power for efficiency improvement of NPLs. Thus, existing literature emphasized that credit risk proxied by NPLs should be treated as a control variable instead of an undesirable output when regressing production and cost functions (Berger & Mester, 1997; Luo & Yao, 2010).

Capital adequacy ratio (*Capital*): The capital adequacy ratio positively contributes to bank efficiency because a higher capital ratio indicates better creditworthiness and more efficient capital risk management power, from which banks benefit and achieve better performance (Luo & Yao, 2010). Using a sample of unbalanced panel data from 2,408 observations of Japanese Shinkin banks for the period from 2009 to 2017, Harimaya and Ozaki (2021) found that financial health is positively related to bank efficiency. What's more, treating the capital tatio as an environmental determinant, Dietsch and Lozano-Vivas (2000) showed the explanatory power of average capital ratio for bank efficiency because it reduces the efficiency differences between France and Spain from 1988 to 1992.

Interest income ratio (*IIR*): The interest income ratio represents banks' income portfolio diversification, with a lower interest income ratio meaning a higher proportion of non-interest income, such as fee and commission income. When a bank's interest income and non-interest income are not highly correlated, a higher portion of non-interest income (lower IIR) contributes to increased stability in the bank's operating income (Harimaya & Ozaki, 2021). Income diversification also results from the diversification of the banking business and asset allocation, which helps mitigate credit risk and portfolios' idiosyncratic risk (Rossi et al., 2009). However, income diversification may be achieved at a cost of diseconomies, leading to lower efficiency. Harimaya and Ozaki (2021) concluded that income portfolio diversification increases Japanese banks' efficiency while Hayden, Porath, and Westernhagen (2007) found that the diversification of assets location doesn't increase German banks' profitability.

4.2.2 Country-specific factors

The above-mentioned factors are regarded as bank-specific traits that determine the individual bank's efficiency, while the country-specific aspects of the banking sector such as the environmental and regulatory conditions may also contribute to the distinctions among cross-country banking structure, industrial competitions, as well as efficiency frontiers eventually (Dietsch & Lozano-Vivas, 2000).

Diverse domestic demand patterns and varying levels of accessibility contribute to differences in input and output prices and then shape peculiar efficiency frontiers (Dietsch & Lozano-Vivas, 2000). On the one hand, potential differences arise from the domestic demand for financial products and services that can be partly characterized by the population density and GNI per capita. On the other hand, the accessibility of banking products and services that can be indexed by the number of branches results in distinct financial inclusion.

Furthermore, the exchange rate (measured in price currency /base currency) has a significant impact on demand. As it rises, the exports of goods and services from the price-currency country become more expensive for consumers in that country, while imports from the base-currency country also become relatively pricier. Additionally, in the context of freely traded currencies and the existence of forward currency contracts, the percentage variance between forward and spot exchange rates also closely aligns with the disparity between the interest rates of the two countries that directly impact the core business of commercial banks.

Bank competitiveness, measured by the Herfindahl-Hirschman index, Lerner index, Boone indicator, and so on, is a well-established industrial character that has an impact on bank efficiency. Due to its interplay with intangibles and with financial technology, the bank's competitiveness will be discussed along with technological factors.

4.2.3 Technological factors

The integration of technology (e.g., big data, cloud computing, artificial intelligence, machine learning, and blockchain services) in the banking industry enabled novel financial products and services (digital advisory and trading systems, peer-to-peer lending, crowdfunding, mobile payment systems, and various forms of cryptocurrency) that have been ascendant during the past decade. These new entrants subverted the industrial chain of the traditional financial system by expanding the possibilities of accessing financial markets, increasing the diversity of products, and reducing managing costs (Financial Stability Board, 2019[14]). As a reaction to their challenge, the banking sector adopted strategic cooperation with financial technology in ways external (M&A, alliance, incubation, and joint venture) and internal investment like R&D activities (Bergek & Norrman, 2008; Cassiman & Veugelers, 2006; De Man & Duysters 2005). Their investment behaviors are a key factor in materially compelling banking IT adoption and fostering technological innovation[15].

From a financial and managerial perspective, the relationship between banks' reactions and bank efficiency triggered our curiosity. Extant literature has developed impacts of technology-driven M&A on stock returns, employing event study and cumulative average abnormal returns (CARs) in the short-term and buy-and-hold average abnormal returns (BHARs) in the long-term (Carlini et al., 2022; Dranev, et al., 2019; Li et al., 2017). However, the literature on the impact of acquired software and technological products reported as intangibles is relatively sparse. Thus, the present study extends existing literature and empirically tests how intangibles affect bank efficiency.

There are contradictory views on the impact of financial technologies. The proponents of the innovation-growth view emphasize that new financial innovation allows cross-geographical financial activities and improves productivity (Berger, 2003), promotes the credit system developed based on big data (Dynan et al., 2006), exhibits better risk management performance (Norden et al., 2014), improves the bank's internal management efficiency, and makes the information communication between departments

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[14] Available at: https://www.fsb.org/wp-content/uploads/S280319.pdf

[15] There is strategic cooperation between big banks and big tech firms. In China, the cooperation between the Bank of China and Tencent, the Industrial and Commercial Bank and JingDong, the Agriculture Bank of China and Baidu, the China Construction Bank and Alibaba. In May 2016, China Everbright Bank (CEB) formed a formal cooperation with Alipay in which users can use a credit score that is calculated according to their consumption at the Alipay platform as the reference for applying for a credit card. By 2021, 13 Chinese commercial banks have established Fintech subsidiaries (Zhao, Li, Yu, Chen & Lee, 2022).

more efficient (IMF, 2017[16]). Additionally, innovation assists banks in distinguishing their products and services from those offered by other financial institutions (Chandy & Tellis, 2000; Teece, 2010). However, the innovation-fragility view which became outstanding from the 2008 financial crisis also alerts a few caveats that technological innovation triggers excessive credit expansion (Brunnermeier, 2009) and increases shadow banks (Buchak et al., 2018), which all lead to financial risk in the banking industry. Using fintech industry development indices and a dataset of China's banking industry over the period from 2003 to 2017, Lee et al. (2021) showed evidence that technological innovation not only improves the cost efficiency of banks but also enhances the technology adopted by Chinese commercial banks by employing stochastic meta-frontier approach. What's more, estimated with the DEA Malmquist method and using data from 113 Chinese domestic commercial banks from 2008 to 2018, Wang et al. (2021) suggested that commercial banks can reduce their operating cost, strengthen risk control capabilities, and thereby enhance comprehensive efficiency and competitiveness.

Industrial competition: In line with the innovation growth view, as banks possess more intangible assets, they can offer a wider range of financial products and services, leading to economies of scale while enhancing their market power and competitiveness. By the quiet-life hypothesis (Berger & Hannan, 1998), banks' efficiency decreases as market power increases because larger banks are managed without cost minimization. However, the ES hypothesis (Berger, 1995) argues that efficiency improves banking profitability and increases concentration[17]. Taken together, bank's competitiveness serves

[16] Available at: https://www.imf.org/external/pubs/ft/ar/2017/eng/pdfs/imf-ar17-english.pdf

[17] Applying a free distribution stochastic frontier analysis (DFA) to the Japanese banking industry period from 1974 to 2005, Homma, Tsutsui, and Uchida (2014) provide evidence that efficiency makes a positive contribution to firm growth (ES hypothesis), while concentration leads to lower bank efficiency simultaneously (Quiet-life hypothesis). The cross-country analysis has contradictory evidence on the relationship between competition and efficiency. Employing DEA and using data from the banking industries of three Nordic countries, Berg et al. (1993) discovered that competition is negatively

as a pathway by which intangible factors impact its efficiency, highlighting the need to address the reverse causality between efficiency and competitiveness.

related to the bank efficiency and productivity of Finland, Norway, and Sweden. In contrast, by applying DFA to 11 OECD countries, Fecher and Pestieau (1993) had controversial findings that competition favors bank efficiency. The discrepancies may stem from the various underlying data sets and different methodologies applied.

4.3 Methodology

The approach herein involves 4 steps. The first two steps are measuring bank efficiency by a stochastic meta-frontier approach (Battese et al., 2004; Huang, et al., 2014; Lee et al., 2021). Steps 3 and 4 are applied to examine the relationship between intangibles and bank efficiency by a fixed effects model, and then to deal with endogeneity problems by an instrumental variable approach.

4.3.1 Measuring banks' efficiency

In the first step, we begin with the regression of individual banks' total costs within a single-country setup to generate national cost frontiers that measure banks' individual cost efficiency. As for the second step, we regress the predicted national cost frontiers to the inputs and outputs within a group of countries altogether to generate a meta-frontier that measures banks' meta-efficiency.

Step 1: Measuring banks' individual efficiency and inefficiency (stochastic frontier analysis, SFA)

$$C_{ijt} = e^{\alpha_{0j}} x_{1,ijt}^{\beta_1} x_{2,ijt}^{\beta_2} \dots x_{k,ijt}^{\beta_k} e^{U_{ijt}+v_{ijt}} \tag{4.1}$$

$$\begin{aligned} ln\left(\frac{C}{w_1 z}\right)_{ijt} &= \alpha_{0j} + \sum_m \beta_m \, ln\left(\frac{y_m}{z}\right)_{ijt} + \sum_r \gamma_r \, ln\left(\frac{w_r}{w_1}\right)_{ijt} + \frac{1}{2}\sum_m \sum_n \xi_{mn} \, ln\left(\frac{y_m}{z}\right)_{ijt} ln\left(\frac{y_n}{z}\right)_{ijt} \\ &+ \frac{1}{2}\sum_r \sum_s \kappa_{rs} \, ln\left(\frac{w_r}{w_1}\right)_{ijt} ln\left(\frac{w_s}{w_1}\right)_{ijt} + \frac{1}{2}\sum_m \sum_r \psi_{mr} \, ln\left(\frac{y_m}{z}\right)_{ijt} ln\left(\frac{w_r}{w_1}\right)_{ijt} + U_{ijt} + v_{ijt} \end{aligned} \tag{4.2}$$

$$\varepsilon_{ijt} = U_{ijt} + v_{ijt} \tag{4.3}$$

$$\boldsymbol{U} = \boldsymbol{\Omega}^{\boldsymbol{T}} \boldsymbol{\omega} \tag{4.4}$$

We first explain the stochastic frontier analysis within single-country setup. The transcendental logarithmic functional form for the cost function (formula 4.2) comes from a Cobb-Douglas function (formula 4.1), where i, j, and t denote bank, country, and time, respectively. $\frac{y_m}{z}$ is a series of bank outputs with $m = 1, \dots, n$. Banks' outputs consist of total loans (y_1) and other earning assets (y_2), and these outputs are normalized by the bank's total assets (z). Total loans ratio $(Loans)$ is the ratio of interest-earning assets of which the major element is loans, to total assets. Other elements of interest-earning assets are advances to banks and customers, reverse repos, securities borrowed and cash collateral, as well as held-to-maturity financial assets. Other earning assets ratio $(Other\ \_Earnings)$ is the ratio of other earning assets to total assets. Other earning assets consist of derivative financial instruments, available for sale, trading at fair value, investment property, investments in associated companies, brokerage receivables, and insurance assets. As for inputs, $\frac{w_r}{w_1}$ is an array of commercial banks' input prices with $r = 1,2,\ldots,s$. Banks' input prices include human capital price (w_1), physical capital price (w_2), and funding price (w_3). The human capital price $(Labor)$ is measured by the ratio of overheads of which the major element is normally salaries, to total assets net of fixed assets, while the physical capital price $(Physical)$ is calculated as the ratio of other operating expenses net of overheads to fixed assets. Funding price $(Funding)$ is represented by the ratio of interest expenses to total deposits and short-term funding. All the input prices are discounted by human capital price $(Labor)$ to ensure price homogeneity. The dependent variable, individual banks' total cost $(Cost)$, is the total amount of three inputs, which is also standardized by each bank's total assets (z) and human capital price $(Labor)$ to reduce heteroskedasticity and to allow banks in various size to have comparably composed residual terms $\left(U_{ijt} + v_{ijt}\right)$ from which the inefficiency and efficiency are calculated. The definition for outputs, inputs, and total cost are shown in Table A4.1 of the Appendix 4.1.

The composed residual term $\left(\varepsilon_{ijt}\right)$ is disentangled into an idiosyncratic error $\left(v_{ijt}\right)$ and an inefficiency term $\left(U_{ijt}\right)$ (formula 4.3). The idiosyncratic error $\left(v_{ijt} \sim N(0, \sigma_v^2)\right)$ is a symmetric disturbance that is independent with inefficiency term (U_{ijt}) and banks' outputs and inputs. This $\left(v_{ijt}\right)$ is the result of beneficial and unbeneficial external events like instruments of production, climatic factors, statistical bias on inputs and outputs, and even luck. The inefficiency term $\left(U_{ijt} \sim N^+\left(\mu\left(\Omega_{ijt}\right),\ \sigma_u^2\left(\Omega_{ijt}\right)\right)\right)$ is in a one-side disturbance that is also independent with the idiosyncratic error $\left(v_{ijt}\right)$ and banks' outputs and inputs. This term (U_{ijt}) is in a non-negative distribution, which reflects banks failing to reach the minimum cost and each bank's cost lies on or above its cost frontier. The inefficiency term (U_{ijt}) results from a collection of technical and economic inefficiency ($\boldsymbol{\Omega}$, Panel A of Table A4.2), such as incompetence and laziness of the employees, as well as the bureaucracy of the organization.

We intend to estimate cost function while assuming a truncated normal distribution (Stevenson, 1980) for inefficiency. The reason is the possible situation that only a few banks are in the most ineffective state, while most banks are in a state that hasn't reached the efficiency frontier. Thus, U_{ijt} is truncated on the right side of 0, with the mean value μ greater than 0. Conditional upon the joint density function of idiosyncratic error (v_{ijt}) and inefficiency term (U_{ijt}), maximum likelihood estimation (MLE) is an efficient method to calculate coefficients and the inefficiency byproduct. Banks efficiency is produced via $e^{-E\left(U_{ijt}|\varepsilon_{ijt}\right)}$. Our SFA is further tested by the monotonicity conditions[18]. The first-order condition satisfies monotonicity and is positive with respect to each output and input price[19].

Step 2: Measuring banks' meta-efficiency and meta-inefficiency (stochastic meta-frontier analysis, meta-SFA)

Depending on the industrial situation and national circumstances, the adoption of technology and access to product materials are varying for banks that belong to different groups (countries), for which one group has a relatively inefficient frontier to other groups.

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[18] Because $sign\left(\frac{\partial C}{\partial X}\right) = sign\left(\frac{\partial \ln C}{\partial \ln X}\right)$ while X is either outputs or input prices, the sign of first-order condition of $\left(\frac{y_1}{z}\right)$, for example, is predicted by $\beta_1 + \sum_{m=1}^{n} \xi_{1m} \ln\left(\frac{y_m}{z}\right)_{ijt} + \sum_{r=1}^{s} \psi_{1r} ln\left(\frac{w_r}{w_1}\right)_{ijt}$.

[19] While we intended to estimate the time-invariant ($\hat{u}_{ijt} = \hat{\alpha}_{0,j} - \hat{\alpha}_{0,ij}$ is estimated with LSDV) and time-variant technical efficiency (Time-varying decay model $u_{ijt} = e^{-\eta(t-T_i)}u_{ij}$ is estimated by MLE.) for the panel data we collected, the convergence results could not be obtained.

The meta-SFA applied in step 2 evaluates the relatively national efficiency and inefficiency by estimating a meta-frontier, the lower boundary from national cost frontiers.

$$C_{ijt} = f^{j}\left(\boldsymbol{X_{ijt}}\right)e^{\varepsilon_{ijt}} \tag{4.2$'$}$$

$$\varepsilon_{ijt} = U_{ijt} + v_{ijt} \tag{4.3$'$}$$

$$\hat{C}_{ijt} = f^{j}\left(\boldsymbol{X_{ijt}}\right)e^{v_{ijt}} \tag{4.5}$$

$$\hat{C}_{ijt} = f^{M}\left(\boldsymbol{X_{ijt}}\right)e^{\varepsilon_{ijt}^{M}} \tag{4.6}$$

$$\varepsilon_{ijt}^{M} = U_{ijt}^{M} + v_{ijt}^{M} \tag{4.7}$$

$$\boldsymbol{U^{M} = \Pi^{T}\delta} \tag{4.8}$$

We rewrite formulas (4.2) and (4.3) in the generalized form of the cost function, formulas (4.2′) and (4.3′). Formula (4.5) is a group-specific cost frontier from formula (4.2′), $f^{j}\left(\boldsymbol{X_{ijt}}\right)$, while $\boldsymbol{X_{ijt}}$ is a vector containing an array of outputs and input prices. Following Huang et al., (2014), we regress the predicted $\hat{C}_{ijt}$ with all countries together, which generates a meta-frontier for all the samples (formula 4.6). Different from Huang et al. (2014), we include the idiosyncratic term $\left(v_{ijt}\right)$ into the predicted $\hat{C}_{ijt}$ when we regress all countries in the second step because the idiosyncratic term may contain factors that break down the national barriers and contribute to the comparability of separating cost frontiers across countries. Also, because the idiosyncratic term has the expected value of zero $(E(v_{ijt}) = 0)$, including the idiosyncratic term into the predicted $\hat{C}_{ijt}$ shouldn't bias our estimation on average. We additionally present results when excluding the idiosyncratic term $\left(v_{ijt}\right)$ in the robustness test. In comparison to step 1, the inefficiency term U_{ijt}^{M} in step 2 results from a collection of national environmental heterogeneity ($\boldsymbol{\Pi}$, Panel B of Table A4.2).

U_{ijt} estimated in the first step is named as banks' individual inefficiency term, while U_{ijt}^{M} estimated in the second step is interpreted as meta-inefficiency. In a similar vein with U_{ijt}, we assume a normal-truncated normal distribution (Stevenson, 1980) for the meta-inefficiency term, U_{ijt}^{M}. They are all independent and identically distributed (IID).

The individual efficiency and meta-efficiency are calculated as $e^{-E\left(U_{ijt}|\varepsilon_{ijt}\right)}$ and $e^{-E\left(U_{ijt}^{M}|\varepsilon_{ijt}^{M}\right)}$ then.

4.3.2 Examining the impact of intangibles

Step 3: Fixed effects model (FE)

Conditioning on the restriction of the efficiency distribution, some prior works on the determinants of efficiency employed a Tobit model, because the dependent variable is restricted within (0, 1). Otherwise, given the postulation of truncated normal distribution for inefficiency term U_{ijt} and U_{ijt}^{M}, we also reconsider the rationality of truncated regression. The inefficiency term is in a truncated normal distribution, but the inefficiency score below the critical value is not truncated or censored, which means our data (inefficiency terms) is the whole sample instead of a sub-sample of which information is partly known, implying that the Tobit model or models with limited dependent variables are not suitable for assessing the determinants of bank efficiency. The present study is conducted with a fixed effects model consequently (formula 4.9). Then, we also conduct a two-way random effects model accompanied by the Breusch-Pagan Lagrange multiplier test and the Hausman test for determining which estimation technique is required. Estimated statistics showed that the two-way fixed effects model is more efficient for our analysis.

Fixed effects model

$$Efficiency_{ijt} = \beta_1 Intangibles_{ijt} + \sum_{k} \beta_k Controls_{k,ijt} + \mu_i + \lambda_t + \epsilon_{ijt} \tag{4.9}$$

Our banking panel data contains both a cross-sectional dimension and a time-series dimension, with i identifying the bank, j denoting country, and t representing time. μ_i denotes unobservable individual-specific effects. λ_t denotes the time-specific effect of each model. ϵ_{ijt} represents stochastic disturbance with IID. This model requires that ϵ_{ijt} is strictly exogenous $\left(E\left(\epsilon_{ijt} \mid \{X_{1ijs}, \ldots, X_{kijs}\}_{s=1}^{T}\right) = 0\right)$.

We employ banks' individual and meta-efficiency which are both multiplied by 100 for comparability as the dependent variables. The main explanatory variable (panel C of Table A4.2) is banks' intangibles excluding goodwill ($Intangibles$), the major element of which is software and patents. One caveat in order as for this measure is the existence of land use rights and trademarks may disturb our empirical results. To assess a more accurate value of technological assets, we also adopt the positive values of the residuals in a regression model that regresses other intangible assets to total assets in the robustness test, because land use rights and trademarks may be related to banks' size and total assets, while technological assets, especially new patents of small and medium banks that are struggling to survive with fintech innovation, may not be strongly associated with their total assets. $Controls_{k,ijt}$ is an array of control variables that are employed to mitigate omitted-variable problems (Panel A and B in Table A4.2). To explore the heterogenous effect of technologies among various types of commercial banks, we additionally regress with interaction-term of the main explanatory variable and a dummy variable, Listed that is 1 for publicly listed banks and 0 otherwise. The Global Fintech Index is controlled to alleviate the spurious correlation problem because fintech industrial competing with the banking sector and compelling incumbent banks to improve innovation and operating efficiency (Lee et al., 2021).

Step 4: Control competitiveness and an instrumental variable approach (IV approach)

$$Lerner_{ijt} = \frac{P_{ijt} - MC_{ijt}}{P_{ijt}} \tag{4.10}$$

The Lerner index (Panel D in Table A2) is employed to assess the effects of a bank's competitive ability in the banking industry. We don't use the Herfindahl-Hirschman Index (HHI) because it is the sum of the squared market share and a measure of market concentration while we cannot measure market share accurately with limited samples. In formula (10), P_{ijt} is the price of banking total output. We measure P_{ijt} by the ratio of banking revenues to total assets while banking revenues are composed of interest income and non-interest income. MC_{ijt} is the marginal cost for banking output. We proxy MC_{ijt}

by the ratio of the total cost to banking revenues. The Lerner index ranges from 0 to 1, indicating the changes from perfect competition to pure monopoly.

To deal with the reverse causality between efficiency and competitiveness, we use an instrumental variable approach that is estimated with a 2-stage least square (2SLS) and the generalized method of moments (GMM). The fixed effects-transformed Lerner index is instrumented by the average and the lagged average value of other banks' fixed effects-transformed Lerner indexes (in the same country simultaneously). A bank's competitiveness may be related to other banks' competitiveness (the mean value of other Lerner indexes), but its efficiency may not be influenced by other banks directly, which satisfies the exclusion restriction. Meantime, we also delve into different measurements of competitiveness in the robustness test (Panel D in Table A4.2).

4.3.3 Data and descriptive statistics

Our data is obtained from multiple sources. The annual accounting data of commercial banks are collected from Orbis, published by Bureau van Dijk. Due to the missing value, data before 2012 are excluded from our sample, and we restrict our sample to banks with at least 3 years of data. Our data focuses on the 624 commercial banks from 4 areas that consist of 30 countries, the European Union (EU, 27 countries), United States (US), Japan (JP), and Mainland China (CN). We exclude The United Kingdom of Great Britain and Northern Ireland (UK), Canada (CA), Australia (AU), and other countries because of the missing value problem and convergence problem. There is a great number of samples from the US in the Orbis database, which may bring bias when we estimate with macro factors. We use random sampling and draw a sample of 156 US commercial banks (the mean value of samples from another 3 areas). These filtering and cleaning procedures eliminate non-representative data and provide a total sample of 5,277 observations over a 10-year period from 2012 to 2021 (Table A4.3). National data to reflect macro conditions are gathered from the World Bank Data Base. The measure for country-level fintech ecosystem, the Global Fintech Index, is supplied by the website of

Findexable[20], which is constructed with cooperation among various partners, such as Crunchbase, Semrush, startup Blink, and so on. We assemble the Global Fintech Index with our banking dataset. The logarithmic treatment for the original Fintech index is taken for interpretability. To eliminate the multicollinearity problem, the residuals (Fintech score) of this Fintech index after regressing on GNI are employed in our analysis.

Table 4.1 presents the descriptive statistics of the variables used in the analysis. The average intangibles ($Intangibles$) is 0.16%, with a maximum value of 1.27%. This describes that compared to earning assets and liquid assets, intangible assets only rationally account for a small percentage of total assets in the banking industry. In European countries, bank intangibles are annually continuously increased, while there is no significant change for other countries (Graph 4.1). Horizontally, the intangibles in listed banks are more than that in unlisted banks in each year (Graph 4.2). On average, 3.90% of total loans is non-performing loans ($NPLR$), while the maximum non-performing loan ratio is up to 16.57%. Regarding the capital structure, commercial banks have a lower capital ratio (EA) and the average EA is 8.71%. This stands that deposits and other liabilities contribute more than 90% of total assets. As for bank profitability, commercial banks have a low probability because the mean ROA is 0.79%. What's more, the interest income (IIR) accounts for the bigger proportion of banks' total revenue comprising interest and non-interest income, with a mean of 71.63% and a volatility of 18.69%. $Listed$ is a dummy variable which is 1 for publicly listed banks, and 0 otherwise. 24% of our observations are gathered from listed banks. Concerning our macro-environmental variables, the average $Fintech\ score$ is 2.66 and the standard deviation is 0.85. Data on the $Fintech\ score$ restricted our sample to 1090 observations, because published data is only available for limited countries and only in 2020 and 2021. We also checked abnormal variables to ensure other variables are within a reasonable range and to provide a good sample basis for empirical analysis.

Before performing the regression analysis, the variance inflation factor (VIF_k) is

[20] Available at: https://findexable.com/gfi-live/

calculated and presented in Table A4.4 in the Appendix 4.1, to identify the amount of multicollinearity among our regressors. VIF_k equals the ratio of the overall model variance in a multiple regression model to the variance of a model that includes only a single independent variable. A higher VIF for a variable indicates a great degree of linear relationship to other regressors, which reduces the statistical significance of regressors. Similarly, a lower $1/VIF$ indicates a high degree of linear relationship to other regressors. In the present study, a VIF above 5 indicates high multicollinearities. Presented VIF in Table A4.4 shows no existence of high multicollinearities.

4.4 Empirical results

4.4.1 Banks' individual efficiency and meta-efficiency

In this section, we begin by illustrating the estimated results of baseline regression. Before discussing the impact of intangibles on bank efficiency, we first delve into banks' individual and meta-efficiency that are generated by meta-SFA. Banks efficiency, grouped by countries, is summarized and reported in Table A4.5. The individual efficiency suggests that US commercial banks are most efficiently operated, which has a mean value of 0.965 and a standard deviation of 0.045. That is followed by the individual efficiency of CN, of which commercial banks have a mean efficiency of 0.948 and volatility of 0.051. The EU has a lower level of efficiency than other countries, of which the efficiencies are 0.881 with a standard deviation of 0.069. There is an increasing tendency in the EU bank efficiency over the last decade, which is portrayed in detail in Graph 4.3.

Meta-efficiency illustrates the efficiency gap between one national cost frontier and the international meta-cost frontier. On average, US and JP commercial banks are operated closer to the inferior meta-cost frontier, while EU and CN commercial banks are operated under that frontier compared with their counterparts from other countries. There is a slight downward shift in CN banking meta-efficiency from 2012 (Graph 4.4). It is noteworthy that this efficiency gap is regarded to be the result of national regulation, natural endowment, and different environmental factors in our study that include but are not limited to the technology adoption of a bank. Analyzing all samples together and estimating the total efficiency for each observation generates similar results that there is relatively higher efficiency in the US and JP banking industry and relatively lower efficiency in the CN banking industry. Our estimated efficiency scores are higher than the findings of previous studies, yet we are aligning with the notion that US commercial banks operate with higher efficiency.

Graph 4.5 and Graph 4.7 show the truncated distribution of estimated individual and meta-inefficiency, while Graph 4.6 and Graph 4.8 show the lognormal distribution of estimated individual and meta-efficiency. It is not normally distributed, but it doesn't mean that data below a specific value is truncated or censored. Thus, we first regress the estimated efficiency within a static panel data model in the next section.

4.4.2 The relationship between intangible assets and individual efficiency

Table 4.2 presents the relationship between intangible assets ($Intangibles$) and banks' individual efficiency. Column (1) shows that banks' individual efficiency is positively related to intangible assets. The one-unit change in $Intangibles$ results in a 1.20 change in the expected value of commercial banks' individual efficiency. However, estimated coefficients after controlling bank-specific factors and Year-fixed effects (Column 2) turned to insignificant results.

The presented study employed the Lerner index to account for the impact of banks' competitive ability as the formula (4.10). A higher Lerner index indicates higher market power and pricing ability. The Lerner index presented in Graph 4.9 demonstrates that most banks have a Lerner index between 0 and 0.5, which is consistent with previous studies. We regress banks' individual efficiency on intangibles while controlling banks' market power ($Lerner\ index$) in columns (3) to (7). To alleviate the endogeneity concerns, the fixed effects-transformed Lerner index is instrumented by the average value of other banks' fixed effects-transformed Lerner indexes (in the same country simultaneously) in column (4) and is instrumented by the average as well as the lagged average value of other banks' fixed effects-transformed Lerner indexes in column (5). The Sargan test and Cragg-Donald Wald F test suggest the validity of instrumental variables at a significance level of 5%. Intangibles make no notable effect on individual efficiency in columns (3) and (4) but turned to significant positive results in column (5) after dealing with endogeneity problems. The interaction term of $\mathrm{Intangible}$ and Listed in columns (6) and (7) represent that there is no significant impact on individual efficiency for both listed and unlisted commercial banks. The reason may be that banks' intangible assets increase at the cost of cutting earning assets down, which may result in unexpected outputs.

4.4.3 The relationship between intangible assets and meta-efficiency

In Table 4.3, overarching results show that the main explanatory variable

($Intangibles$) is positively related to banks' meta-efficiency. Estimated results are significantly positive when bank meta-efficiency is regressed on the intangible assets (Column 1). The one-unit change in $Intangibles$ results in a 0.832 change in the expected value of commercial banks' meta-efficiency. However, estimated coefficients after controlling bank-specific factors and Year-fixed effects (Column 2) turned to insignificant results. In columns (3) to (5), results are consistent with former results that intangible assets positively predict meta-efficiency when dealing with omitted variable bias and mitigating the endogeneity concerns by controlling banks' competitiveness and estimated with IV approaches.

The coefficients of interaction terms are significantly positive after controlling banks' competitiveness in columns (6) and (7), demonstrating that intangible assets contribute to the meta-efficiency of both listed and unlisted banks. Compared to their unlisted counterparts, the impact of intangible assets on meta-efficiency is more pronounced for listed commercial banks. Listed commercial banks are holding much more intangible assets and may be good at utilizing new technology products to achieve economies of scale. They also have more human and financial resources to conduct R&D or purchase technology-related assets than unlisted commercial banks, implying less burden for them to increase technology adoption and generate higher efficiency.

These results emphasize that macro-environmental factors that determine inefficiency can be ameliorated by banks' intangible assets. For instance, in virtue of the technological implication in the financial industry, banks reallocate their input materials more efficiently depending upon different domestic demands.

4.4.4 Robustness test

Robustness test with a stochastic approach to measure competitiveness

There are various methods to capture industrial competition due to the complex notion of competitive ability and market power. Instead of approximating a firm's marginal costs using the ratio of average costs, banks' marginal costs can be calculated from a trans-log cost function (Coccorese, 2014). Thus, we calculate the stochastic Lerner index concerning total loans and other earning assets through a stochastic approach (Appendix 4.2).

We first regress competitive measures (including the Lerner index, Lerner index of total loans, and other earning assets) on banks' intangible assets, and the estimated results are reported in Table 4.4. The coefficients of *Intangibles* are negative at a significant level with controlling bank-specific factors, country-specific factors, and two-way fixed effects. The inhibitory impact on banks' competitive ability may result from the cost of cutting earning assets down and the diseconomies of a variety of financial products and services.

Presented results in Table 4.5 are estimated by controlling different measures for competitive ability, the Lerner index for total loans as well as the Lerner index with respect to other earning assets. They are instrumented by the average and the lagged average value of other banks' fixed effects-transformed Lerner index for total loans and other earning assets and are estimated with 2SLS (Columns 2 and 5) and GMM (Columns 3 and 6). Estimated results show that though positive impact on individual efficiency, the coefficients of *Intangibles* are not at a significant level. However, after controlling competitive ability and eliminating the endogeneity concern, results in columns (5) and (6) provide evidence that intangible assets have a positive relationship with their meta-efficiency, which is robust and in line with the results in Table 4.3.

Robustness test with alleviating accuracy concerns

As mentioned in the section on Methodology, some accuracy concerns are in order. First, to assess a more accurate value of technological factors in intangible assets, we also adopt the positive values of the residuals after regressing other intangible assets to total assets in the robustness test. This restricted our sample to 905 observations, and only 693 observations when estimating with an IV approach (Table 4.6). The results are estimated with both 2SLS and GMM and show that this alternative measure for the intangible assets (*Intangibles_pred*) positively predicts bank individual and meta-efficiency at a significant level.

Another caveat is that fintech industrial competing with the banking sector and compelling incumbent banks to improve innovation and operating efficiency (Lee et al., 2021). Thus, simply regressing efficiency scores on the intangible assets may generate a spurious correlation problem. As for this concern, we should emphasize that controlling banks' competitiveness ($Lerner\ index$) has already controlled the impact of the fintech industry on banks' competitive ability. To further eliminate concerns that financial technology impacts bank efficiency via other mechanisms, we additionally controlled the Global Fintech Index, which restricted our sample to 1,090 observations, because data of the Global Fintech Index are available for limited countries and only in 2020 and 2021. The results show that the intangible assets ($Intangibles$) positively predict meta-efficiency for listed banks at a significant level but have no notable impact on individual efficiency (Columns 1 and 2 in Table 4.7).

We included the idiosyncratic term (v_{ijt}) into the predicted $\hat{C}_{ijt}$ when we regress all countries in the second step. We also present results when excluding the idiosyncratic term (v_{ijt}) here. The coefficient of the intangible assets ($Intangibles$) in columns (3) and (4) of Table 4.7 is significantly positive. Finally, column (5) present how intangible assets influence banks' total efficiency of which banks' total efficiency is generated when regressing all samples together. The coefficients of the $Intangibles$ suggest that banks' total efficiency increases in their intangible assets.

Taken together, banks' intangible assets increase their efficiency, and the fostering effects act more on the improvement of meta-efficiency. The plausible explanation for our finding is the amelioration of macro-environmental restrictions. Compared to their unlisted counterparts, the impact of intangible assets on meta-efficiency is more pronounced for listed commercial banks for the less burden to increase technology adoption and generate higher efficiency. Bank's intangible assets also positively predict their individual efficiency, albeit inconclusive and not vary robust. One conceivable explanation is that banks' core business activities and services are cut down to increase intangible assets, leading to lower output and individual efficiency scores.

4.5 Further analysis with efficiency convergence

The improvement of meta-efficiency and the amelioration of macro-environmental restrictions triggers our research curiosity on efficiency convergence. Put another way, the elimination of national restrictions on bank efficiency should contribute to perfect competition and accelerate efficiency convergence. Barro and Sala-I-Martin (1991) propose a concept of convergence, beta convergence[21], that is the regress of the growth rate (formula 4.11) on the initial level for any variable (formula 4.12). Beta convergence implies that countries with a lower level of bank efficiency have faster growth rates than countries with a higher level of bank efficiency. Thus, beta-type convergence exists when the growth rate is negatively correlated with the initial value.

$$Dif_{ijt} = lnEFF_{ijt} - lnEFF_{ij,t-1} \tag{4.11}$$

$$Dif_{ijt} = \alpha_0 + \beta_{Convergence} lnEFF_{ij,t-1} + \beta_{Intangible} lnEFF_{ij,t-1} \times Intangible + \sum_{t=2012}^{2021} \beta_t D_t + \zeta_{ijt} \tag{4.12}$$

EFF_{ijt} is the cost efficiency scores of banks of country i of country j in year t[22], $EFF_{ij,t-1}$ is the cost efficiency scores of banks of country i in year $t-1$, D_{i} is the country dummies, ζ_{ijt} the error term, and α_0 and $\beta_{convergence}$ the parameters to be estimated. Due to the limited observation of generated $\beta_{convergence}$, we employ the interaction term ($lnEFF_{ij,t-1} \times Intangibles$) to examine whether the marginal effect of $lnEFF_{ij,t-1}$ depends on the $Intangibles$, rather than conducting the regression analysis between $\beta_{convergence}$ and $Intangible$.

The individual and meta-efficiency differences (Dif_{ijt}) are regressed on their lagged efficiency, intangibles, as well as interaction terms. Estimated results are reported in

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[21] Due to the limitation of dataset, we didn't talk about Sigma convergence which is observed if each country's level of bank efficiency is converging to the average level of the group of countries.

[22] Due to the limitation of data, we regress with the original efficiency score instead of the mean cost efficiency score.

Tables 4.8 and 4.9. The negative coefficients of lagged efficiency ($L.Individual\ efficiency$, $L.Meta-efficiency$) imply the existence of beta-type convergence (Columns 1 in Tables 4.8 and 4.9). The coefficients of interaction terms ($L.Individual\ efficiency\ *\ Intangibles$) of individual efficiency and intangibles are significantly positive (Column 2) but turned to insignificantly negative after controlling the bank and nation-specific factors (Column 3), and turned to significantly negative after controlling Fintech score. The coefficients of interaction terms ($L.Meta-efficiency\ *\ Intangibles$) of meta-efficiency and intangibles are significantly negative (Columns 2 to 4) even after controlling the bank and nation-specific factors, and the Fintech score (Column 6), demonstrating that banks' intangible assets have a positive impact on meta-efficiency convergence.

Finally, the total efficiency difference is regressed on their lagged efficiency, intangibles, as well as interaction terms in Table 4.10. The negative coefficients of lagged efficiency ($L.Total\ efficiency$) reconfirm the existence of beta-type convergence. We additionally control bank and country-specific factors in column (3), and Fintech score in column (4). The marginal effect of $lnEFF_{ij,t-1}$ depends on the $Intangibles$ because the coefficients of the interaction term ($L.Total\ efficiency * Intangibles$) are significantly negative, which confirms the relationship between intangible assets and efficiency convergence.

Another finding is the significantly negative coefficients of interaction terms of individual efficiency and Global Fintech score index ($L.Individual\ efficiency * Fintech\ score$ in Table 4.8), and significantly positive coefficients of interaction terms of meta-efficiency and Global Fintech score index, ($L.Total\ efficiency * Fitnech\ score$ in Table 4.10). Although $Finech\ score$ has no notable effect on efficiency in Table 4.7, Tables 4.8 to 4.9 show that the fintech industry improves individual efficiency convergence while inhibiting meta-efficiency convergence. One of the reasons may be that fintech bring challenges and differentiates incumbent commercial banks. But it is the banks' response to technology (such as purchased technological assets and others) that homogenizes this differentiation, promotes meta-convergence, and improves perfect competition of markets.

4.6 Conclusions and limitations

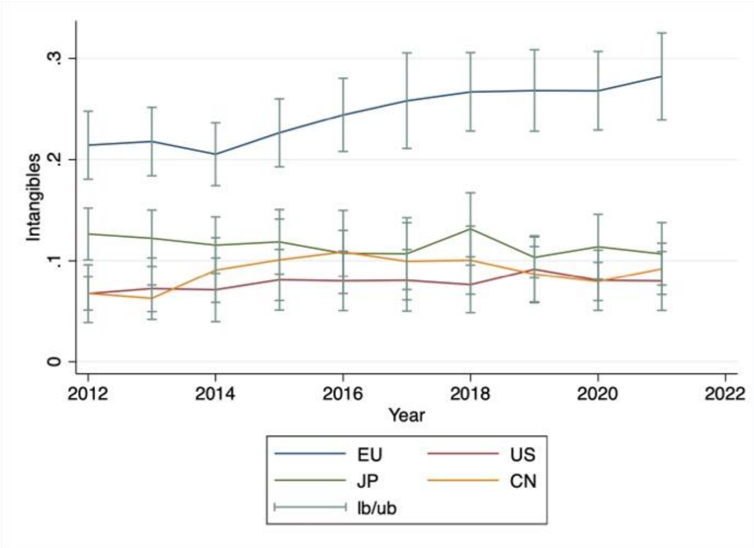
Intangibles are growing crucial for commercial banks in a knowledge-driven economy. The present study provides empirical evidence for the relationship between a bank efficiency and its identifiable intangibles that mainly contain software after excluding goodwill. Our findings indicate that intangible assets enhance bank efficiency, with the fostering effects being more pronounced in improving meta-efficiency. Additionally, intangibles show a positive association with individual efficiency, although the evidence is not entirely conclusive and robust. Furthermore, within the context of varying competition (or cooperation) and differentiation among incumbent commercial banks resulting from the level of national fintech development, intangible assets play a crucial role in fostering perfect competition and accelerating the convergence of efficiency. One of the rational explanations for our findings is the technology-related acquisition and procurement that are reported as intangibles on the balance sheet. Because the purchased software and technological products are means of acquiring digital transformations which can contribute to the mitigation of information asymmetry and the amelioration of macro-environmental restrictions.

Our findings hold practical significance from an economic perspective. While larger and publicly listed banks tend to provide more detailed disclosure of intangible assets, there are still many banks that lack comprehensive reporting in this regard. However, in today's increasingly technology-driven and research-oriented landscape, it is crucial to be more detailed in accounting disclosure regarding external technology-related investment, and internal technology-related R&D. Being akin to M&A and R&D, intangible assets also reflect organizational strategies. Therefore, more comprehensive accounting disclosure is beneficial for strengthening external monitoring and enabling accurate evaluations.

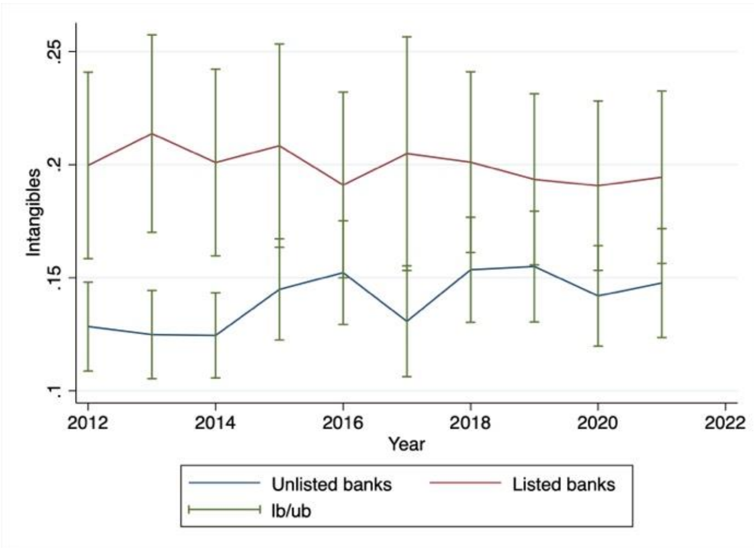
Our work does have some limitations. We employed two-stage analysis methods that are estimating efficiency first and examine their relationship with intangibles second, to assess the impact of intangible assets. One reason for this approach is to address endogeneity concerns while controlling for banks' competitive ability. Further research could explore simultaneous estimation approaches and integrate steps 3 and 4 into steps 1 and 2. What's more, various methods such as different models of SFA and DEA, can be employed to evaluate bank efficiency to generate accurate and robust conclusions.

Graphs and Tables

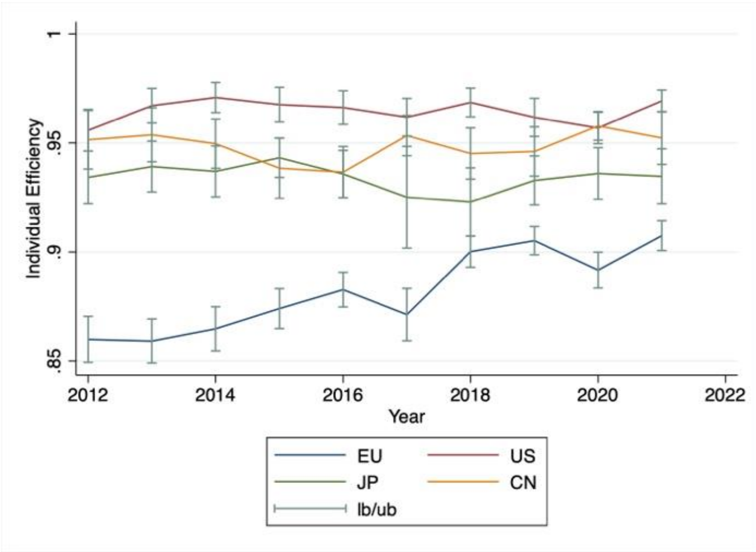
The graphs and tables discussed in the present study are displayed here.



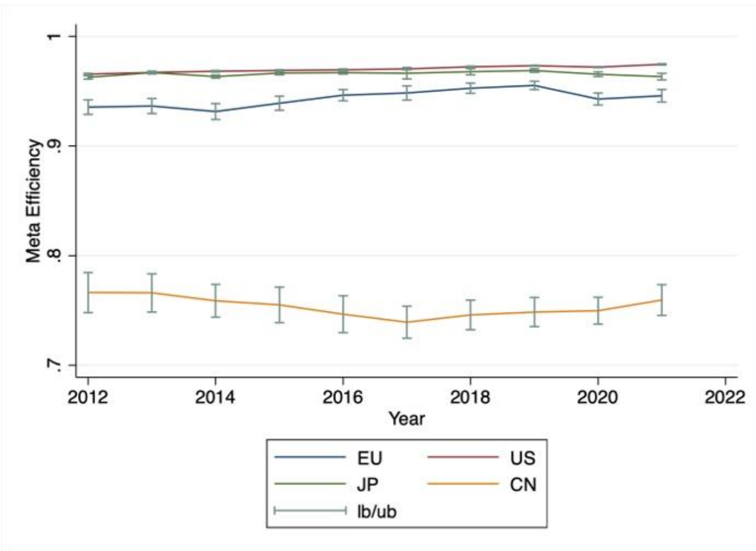
Graph 4.1 Bank intangible assets tendency of each country



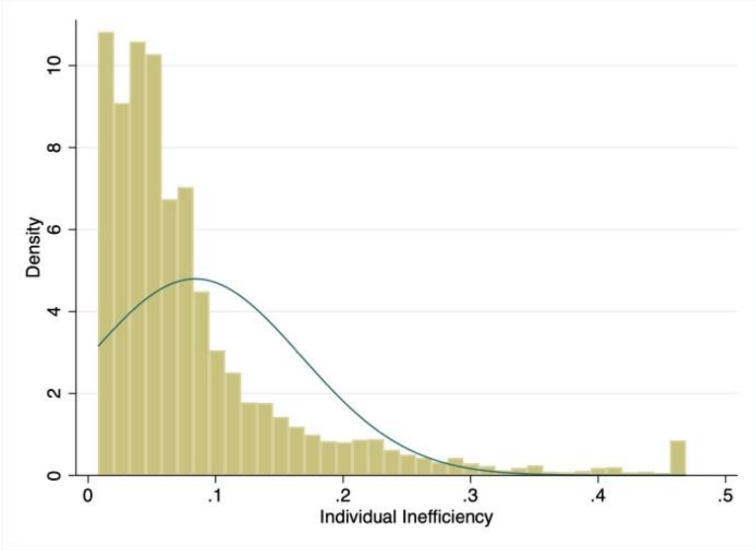
Graph 4.2 Bank intangible assets tendency of listed and unlisted banks



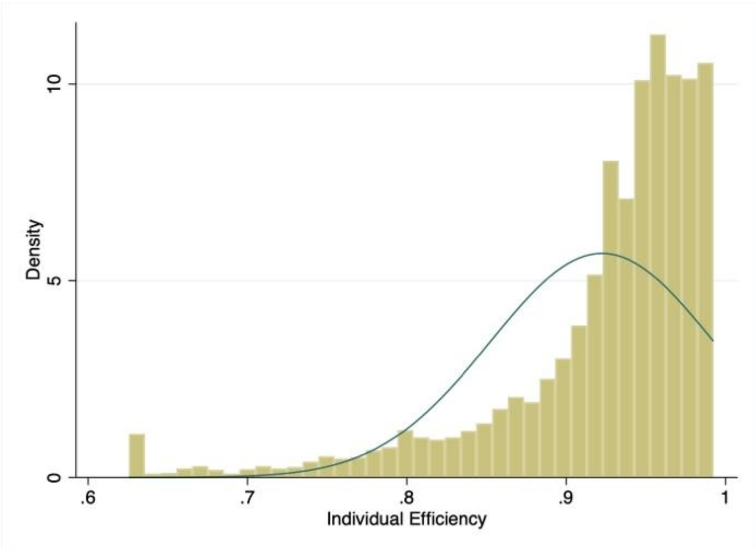
Graph 4.3 Bank individual efficiency tendency



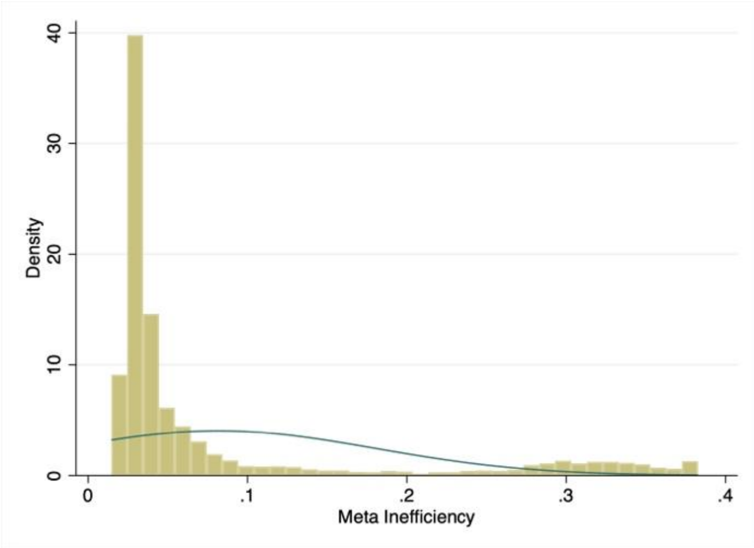
Graph 4.4 Bank meta-efficiency tendency



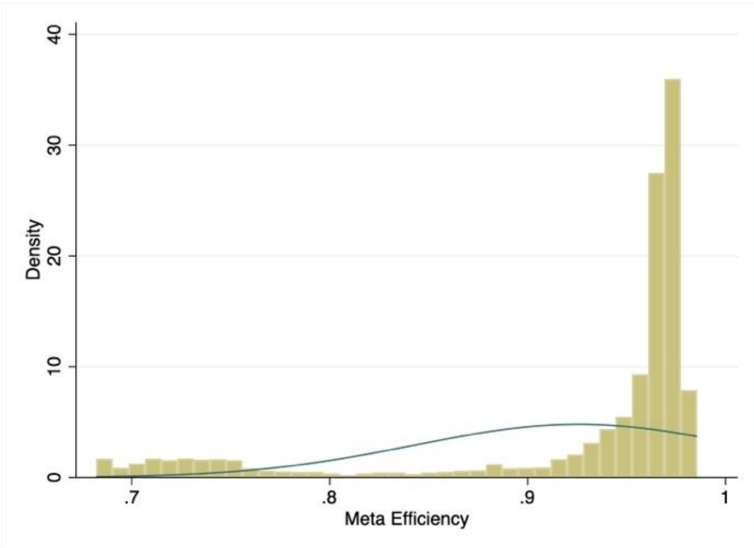
Graph 4.5 Bank individual inefficiency distribution



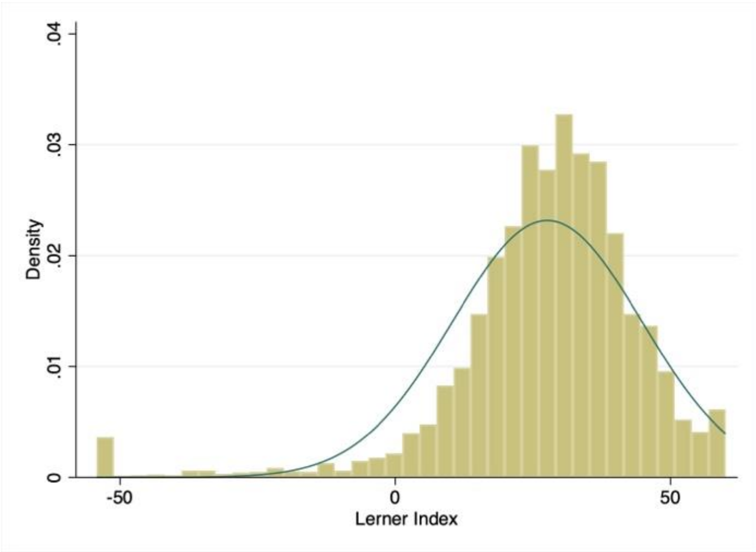
Graph 4.6 Bank individual efficiency distribution



Graph 4.7 Bank meta-inefficiency distribution



Graph 4.8 Bank meta-efficiency distribution



Graph 4.9 Lerner index distribution

Table 4.1 Descriptive statistics

Variable	Obs	Mean	Std. dev.	Min	Max
Main explanatory variables					
Intangibles	5,277	0.155	0.230	0.000	1.270
Intangibles _ pred	905	0.250	0.353	0.001	3.985
Fintech development factors					
Fintech score	1,090	20.541	21.594	1.235	69.151
Competitiveness measures					
Lerner index	5,277	27.608	17.217	-54.250	60.007
Lerner index of total loans	5,277	19.939	24.181	2.911	163.438
Lerner index of other earning assets	5,277	19.969	23.673	2.988	160.538
Instrumental variables					
Other banks' mean Lerner index	5,277	27.608	4.698	18.846	36.080
Other banks' mean Lerner index of total loans	5,277	19.939	8.704	4.989	32.884
Other banks' mean Lerner index of other earning assets	5,277	19.969	8.386	5.277	35.591
Control variables					
NPLR	5,277	3.895	4.585	0.000	16.570
EA	5,277	8.706	3.824	3.813	24.673
IIR	5,277	71.627	18.688	23.058	103.829
ROA	5,277	0.788	0.850	-2.743	3.499
Listed	5,277	0.242	0.429	0.000	1.000
Branches	5,277	0.291	0.126	0.040	0.839
GNI	5,277	38.304	19.619	5.910	87.950
Population	5,277	0.158	0.149	0.018	1.610
Exchange	5,277	24.452	48.248	0.529	307.997

Notes: Data about commercial banks is collected from 30 countries over a 10-year period from 2012 to 2021. We winsorize the values beyond the limits of 1% and 99% and restrict our sample to banks with at least 3 years of data.

Table 4.2 Relationship between individual efficiency and intangible assets: baseline regression

Dependent variable	Individual efficiency						
	(1) Fixed effects	(2) Fixed effects	(3) Fixed effects	(4) 2SLS	(5) GMM	(6) Fixed effects	(7) 2SLS
Intangibles	**1.196****	**-0.106**	**0.237**	**0.500**	**0.858***		
	(2.28)	**(-0.26)**	**(0.60)**	**(1.22)**	**(1.84)**		
0.Listed * Intangibles						**-0.009**	**0.319**
						(-0.02)	**(0.71)**
1.Listed * Intangibles						**1.349**	**1.319**
						(1.62)	**(1.56)**
Lerner index			0.101***	0.178***	0.165***	0.101***	0.178***
			(16.24)	(6.16)	(7.41)	(16.18)	(6.16)
NPLR		-0.680***	-0.622***	-0.578***	-0.578***	-0.621***	-0.577***
		(-31.94)	(-29.61)	(-21.56)	(19.93)	(-29.52)	(-21.58)
EA		0.100***	0.130***	0.152***	0.093***	0.133***	0.154***
		(3.36)	(4.45)	(4.95)	(2.71)	(4.55)	(5.03)
IIR		0.014**	0.020***	0.024***	0.020***	0.020***	0.024***
		(2.54)	(3.69)	(4.26)	(3.07)	(3.71)	(4.28)
ROA		2.878***	1.262***	0.026	0.413	1.269***	0.029
		(34.72)	(9.85)	(0.05)	(1.15)	(9.90)	(0.06)

(*Continued on the next page*)

Table 4.2 Continued

_cons	92.059***	90.333***	88.210***	86.586***		88.146***	86.536***
	(966.32)	(181.54)	(175.94)	(110.7)		(175.23)	(111.18)
Instruments	No	No	No	Mean	Mean & Lagged	No	Mean
Bank-fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed	No	Yes	Yes	Yes	No	Yes	Yes
N	5277	5277	5277	5277	4215	5277	5277
R-squared	0.001	0.429	0.460	NA	0.460	0.460	NA

*Notes: Table 4.2 examines the relationship between individual efficiency and intangible assets. The present study uses an analyzing power of 10%, which means the null hypothesis (H_0:Intangible assets have no impact on the efficiency of commercial banks) will be rejected if the t value in the critical region is 5% for each side. *, **, *** are designated for the level of significance of 10%, 5% and 1%, respectively. We perform the Hausman test (1978) to choose between the fixed effects model and random effects model, which indicates that the fixed effects model is more efficient than random effects in our analysis (F-test and Breusch-Pagan Lagrange multiplier test also indicate the efficiency of these two models when being compared to pooled OLS). The dependent variable is commercial banks' individual efficiency, while the main explanatory variable is intangible assets (Intangibles). Columns (2) and (3) additionally control bank-specific traits, year-fixed effects, and competitiveness measured by the Lerner index. To deal with the endogeneity problem, the Lerner index is instrumented by the average value of other banks' fixed effects-transformed Lerner indexes and estimated with 2SLS in columns (4). Column (5) is instrumented by the average value and the lagged average value of the fixed effects-transformed Lerner index while being estimated with GMM. Columns (6) and (7) test the heterogeneous effects via the interaction term between Listed and Intangibles. The Sargan test for over-identifying restriction and the Cragg-Donald Wald F test for weak identification suggests the validity of instrumental variables at a significance level of 5%.*

Table 4.3 Relationship between meta-efficiency and intangible assets: baseline regression

Dependent variable	Meta-efficiency						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Fixed effects	Fixed effects	Fixed effects	2SLS	GMM	Fixed effects	2SLS
Intangibles	**0.832****	**0.292**	**0.746****	**1.042*****	**1.234*****		
	(2.42)	**(0.86)**	**(2.27)**	**(2.92)**	**(3.09)**		
0. Listed * Intangibles						**0.651***	**0.956****
						(1.83)	**(2.49)**
1. Listed * Intangibles						**1.180***	**1.438****
						(1.68)	**(1.99)**
Lerner index			0.062***	0.103***	0.097***	0.062***	0.103***
			(19.51)	(5.96)	(6.40)	(19.51)	(5.96)
Branches		-11.396***	-5.242***	-1.219	-2.902*	-5.221***	-1.204
		(-8.56)	(-3.98)	(-0.57)	(-1.73)	(-3.96)	(-0.56)
GNI		0.021*	-0.002	-0.017	0.011	-0.002	-0.017
		(1.75)	(-0.17)	(-1.27)	(0.99)	(-0.17)	(-1.27)
Population		-3.282	1.751	5.040	4.501	1.898	5.172
		(-0.78)	(0.43)	(1.17)	(0.68)	(0.47)	(1.20)
Exchange rate		0.032***	0.003	-0.016	-0.025**	0.003	-0.016
		(4.30)	(0.44)	(-1.44)	(-2.07)	(0.45)	(-1.44)

(Continued on the next page)

Table 4.3 Continued

_cons	92.450***	95.005***	92.133***	90.256***		92.091***	90.219***
	(1478.07)	(103.81)	(103.30)	(75.32)		(103.01)	(75.25)
Instruments	No	No	No	Mean	Mean & Lagged	No	Mean
Bank-fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed	No	Yes	Yes	Yes	No	Yes	Yes
N	5277	5277	5277	5277	4215	5277	5277
R-squared	0.001	0.034	0.107	NA	0.103	0.108	NA

*Notes: Table 4.3 examines the relationship between individual efficiency and intangible assets. The present study uses an analyzing power of 10%, which means the null hypothesis (H_0:Intangible assets have no impact on the efficiency of commercial banks) will be rejected if the t value in the critical region is 5% for each side. *, **, *** are designated for the level of significance of 10%, 5% and 1%, respectively. We perform the Hausman test (1978) to choose between the fixed effects model and random effects model, which indicates that the fixed effects model is more efficient than random effects in our analysis (F-test and Breusch-Pagan Lagrange multiplier test also indicate the efficiency of these two models when being compared to pooled OLS). The dependent variable is commercial banks' meta-efficiency, while the main explanatory variable is intangible assets (Intangibles). Columns (2) and (3) additionally control bank-specific traits, year-fixed effects, and competitiveness measured by the Lerner index. To deal with the endogeneity problem, the Lerner index is instrumented by the average value of other banks' fixed effects-transformed Lerner indexes and estimated with 2SLS in columns (4). Column (5) is instrumented by the average value and the lagged average value of the fixed effects-transformed Lerner index while being estimated with GMM. Columns (6) and (7) test the heterogeneous effects via the interaction term between Listed and Intangibles. The Sargan test for over-identifying restriction and the Cragg-Donald Wald F test for weak identification suggests the validity of instrumental variables at a significance level of 5%.*

Table 4.4 Relationship between competitiveness and intangible assets

Dependent variables	Lerner index	Lerner index of total loans	Lerner index of other earning assets
	(1) Fixed effects	(2) Fixed effects	(3) Fixed effects
Intangibles	**-4.247*** **	**-4.650** **	**-4.943** **
	(-4.60)	**(-2.21)**	**(-2.42)**
NPLR	-0.482***	0.219*	0.127
	(-9.73)	(1.94)	(1.16)
EA	-0.287***	-0.377**	-0.302**
	(-4.22)	(-2.43)	(-2.01)
IIR	-0.063***	-0.111***	-0.094***
	(-5.03)	(-3.88)	(-3.37)
ROA	15.883***	8.834***	8.497***
	(82.11)	(20.09)	(19.87)
Branches	-35.223***	23.271***	10.422
	(-9.60)	(2.79)	(1.28)
GNI	-0.106***	-0.180**	-0.182**
	(-3.16)	(-2.36)	(-2.46)
Population	3.268	-17.929	-21.275
	(0.29)	(-0.70)	(-0.86)
Exchange rate	0.073***	0.019	0.035
	(3.51)	(0.40)	(0.76)
_cons	34.858***	23.219***	26.457***
	(13.10)	(3.84)	(4.50)
Bank-fixed	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes
N	5277	5277	5277
R-squared	0.678	0.107	0.107

*Notes: Employing a fixed effects model, Table 4.4 examines the relationship between intangible assets and competitiveness measured by the Lerner index in column (1), the Lerner index of total loans in column (2), and the Lerner index of other earning assets in column (3). The present study uses an analyzing power of 10%, which means the null hypothesis (H_0:Intangible assets have no impact on the competitiveness of commercial banks) will be rejected if the t value in the critical region is 5% for each side. *, **, *** are designated for the level of significance of 10%, 5% and 1%, respectively.*

Table 4.5 Relationship between efficiency and intangible assets: robustness test

Dependent variables	Individual efficiency			Meta-efficiency		
	(1) Fixed effects	(2) 2SLS	(3) GMM	(4) Fixed effects	(5) 2SLS	(6) GMM
Intangibles	**-0.027**	**0.041**	**0.972**	**0.401**	**0.765***	**0.824***
	(-0.07)	**(0.05)**	**(1.29)**	**(1.18)**	**(1.86)**	**(1.90)**
Lerner index of total loans	-0.009	-0.735	-0.522*	0.006	0.127	0.050
	(-1.52)	(-1.20)	(-1.90)	(1.06)	(0.27)	(0.27)
Lerner index of other earning assets	0.024***	0.767	0.592**	0.010*	-0.058	0.004
	(3.84)	(1.31)	(2.21)	(1.89)	(-0.12)	(0.02)
NPLR	-0.681***	-0.597***	-0.621***			
	(-32.04)	(-6.85)	(-11.17)			
EA	0.104***	0.055	-0.022			
	(3.50)	(0.64)	(-0.29)			
IIR	0.015***	0.002	-0.004			
	(2.79)	(0.10)	(-0.26)			
ROA	2.755***	2.799***	2.474***			
	(31.90)	(4.08)	(6.43)			
Branches				-11.216***	-11.979*	-9.734***
				(-8.45)	(-1.83)	(-3.48)
GNI				0.021*	0.017	0.017
				(1.68)	(1.26)	(1.38)

(Continued on the next page)

Table 4.5 Continued

Population				-2.327	0.663	-3.159
				(-0.56)	(0.13)	(-0.46)
Exchange rate				0.029***	0.020	0.014
				(3.88)	(1.60)	(1.29)
_cons	90.027***	90.743***		94.603***	93.702***	
	(179.94)	(39.24)		(103.55)	(38.08)	
Instruments	No	Mean	Mean & Lagged	No	Mean	Mean & Lagged
Bank-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	No	Yes	Yes	No
N	5277	5277	4215	5277	5277	4215
R-squared	0.433	NA	-0.342	0.043	NA	-0.012

*Notes: Table 4.5 examines the relationship between individual efficiency and intangible assets (Columns 1 to 3), and the relationship between meta-efficiency and intangible assets (Columns 4 to 6). The present study uses an analyzing power of 10%, which means the null hypothesis (H_0:Intangible assets have no impact on the efficiency of commercial banks) will be rejected if the t value in the critical region is 5% for each side. *, **, *** are designated for the level of significance of 10%, 5% and 1%, respectively. The dependent variable is commercial banks' individual efficiency (Columns 1 to 3) and meta-efficiency (Columns 4 to 6), while the main explanatory variable is intangible assets (Intangibles). We control competitiveness measured by the Lerner index of total loans and the Lerner index of other earning assets in each column. They are instrumented by the average value of other banks' fixed effects-transformed Lerner index, estimated with 2SLS in columns (2) and (5). Columns (3) and (6) are instrumented by the average and the lagged average value of other banks' fixed effects-transformed Lerner index, and are estimated with GMM. The Sargan test and Cragg-Donald Wald F test suggest the validity of instrumental variables at a significance level of 5%.*

Table 4.6 Robustness test with alleviating accuracy concerns

Dependent variables	Individual efficiency		Meta-efficiency	
	(1) 2SLS	(2) GMM	(3) 2SLS	(4) GMM
Intangibles_pred	**2.655****	**1.394****	**1.041***	**1.917*****
	(2.50)	**(1.98)**	**(1.86)**	**(2.59)**
Lerner index	0.370***	0.154***	0.117**	0.186***
	(3.31)	(3.48)	(2.32)	(4.51)
NPLR	-0.548***	-0.613***		
	(-8.02)	(-12.07)		
EA	0.147	-0.096		
	(1.35)	(-1.13)		
IIR	0.077***	0.058***		
	(3.74)	(3.54)		
ROA	-2.280	1.270*		
	(-1.27)	(1.73)		
Branches			2.182	3.482
			(0.49)	(0.94)
GNI			-0.006	0.010
			(-0.08)	(0.21)
Population			12.333	20.723
			(1.08)	(1.52)
_cons	78.311***		-0.054	-0.115***
	(24.07)		(-1.55)	(-3.40)
Instruments	Mean	Mean & Lagged	Mean	Mean & Lagged
Bank-fixed	Yes	Yes	Yes	Yes
Year-fixed	Yes	No	Yes	No
N	905	693	905	693
R-squared	NA	0.680	NA	0.057

*Notes: Table 4.6 reports the robustness test using the predicted intangible assets (Intangibles_pred). The t statistics are reported in parentheses. The present study uses an analyzing power of 10%, which means the null hypothesis (H_0:Intangible assets have no impact on the efficiency of commercial banks) will be rejected if the t value in the critical region is 5% for each side. *, **, *** are designated for the level of significance of 10%, 5% and 1%, respectively. Dependent variables are individual efficiency (Columns 1 and 2), and meta-efficiency (Columns 3 and 4). Banks' competitiveness is measured by the Lerner index and instrumented by the mean and lagged mean value of other banks' fixed effects-transformed competitiveness. The Sargan test and Cragg-Donald Wald F test suggest the validity of instrumental variables at a significance level of 5%.*

Table 4.7 Robustness test with alleviating accuracy concerns

Dependent variables	Individual efficiency	Meta-efficiency	Meta-efficiency without error term		Total efficiency
	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) GMM
Intangibles			**0.381***	**0.438***	**3.601*****
			(1.83)	**(1.93)**	**(3.36)**
0.Listed * Intangibles	**-31.861**	**0.125**			
	(-0.54)	**(0.01)**			
1.Listed * Intangibles	**11.495**	**10.704***			
	(0.40)	**(1.89)**			
Lerner index			0.002		0.491***
			(0.23)		(6.83)
Lerner index of total loans	-1.382	0.135		0.069	-0.023
	(-0.44)	(0.38)		(0.26)	(-1.14)
Lerner index of other earning assets	1.331	0.004		-0.058	
	(0.29)	(0.03)		(-0.22)	
Fintech score	0.253	-0.124			
	(0.02)	(-0.23)			
NPLR	-0.856				0.054
	(-0.90)				(0.81)
EA	-0.704				0.275***
	(-0.18)				(3.50)
IIR	0.073				0.095***
	(0.27)				(6.33)

(Continued on the next page)

Table 4.7 Continued

ROA	3.516				-3.733***
	(0.10)				(-3.27)
Branches			2.311*	1.334	-8.005
			(1.85)	(0.37)	(-1.54)
GNI		-0.167	0.012	0.012	-0.112***
		(-0.55)	(1.51)	(1.58)	(-3.85)
Population			-6.385**	-6.056**	-6.248
			(-2.53)	(-2.20)	(-0.37)
Exchange rate		-0.128	0.014**	0.014**	-0.003
		(-1.12)	(2.20)	(2.02)	(-0.11)
_cons	96.957	99.861***	94.216***	94.331***	
	(1.36)	(14.98)	(134.92)	(69.11)	
Instruments	Mean	Mean	Mean	Mean	Mean & Lagged
Bank-fixed	Yes	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes	No
N	1090	1090	5277	5277	4215
R-squared	NA	NA	NA	NA	0.120

*Notes: Table 4.7 reports various robustness tests. The t statistics are reported in parentheses. The present study uses an analyzing power of 10%, which means the null hypothesis (H_0:Intangible assets have no impact on the efficiency of commercial banks) will be rejected if the t value in the critical region is 5% for each side. *, **, *** are designated for the level of significance of 10%, 5% and 1%, respectively. Columns (1) and (2) are estimated by additionally controlling the national Fintech development level (Fintech score). Dependent variable in columns (3) and (4) is an alternative meta-efficiency estimated without error term (v_{ijt}) in formula (7). The dependent variable in Columns (5) is total efficiency with all countries estimated together. The Sargan test and Cragg-Donald Wald F test suggest the validity of instrumental variables at a significance level of 5%.*

Table 4.8 The relationship between intangible assets and individual efficiency convergence

Dependent variables	Individual efficiency difference			
	(1) Fixed effects	(2) Fixed effects	(3) Fixed effects	(4) Fixed effects
L. Individual efficiency	-0.633***	-0.683***	-0.813***	-0.881***
	(-40.70)	(-35.99)	(-51.52)	(-7.63)
Intangibles		-19.857***	5.322	30.424*
		(-4.46)	(1.45)	(1.79)
L. Individual efficiency * Intangibles		0.221***	-0.056	-0.435**
		(4.56)	(-1.40)	(-2.38)
Fintech score				11.029***
				(3.46)
L. Individual efficiency * Fintech score				-0.119***
				(-3.41)
NPLR			-0.551***	-0.936***
			(-21.12)	(-8.74)
EA			0.048	-0.233
			(1.40)	(-1.46)
IIR			0.010	0.094***
			(1.61)	(4.24)
ROA			3.090***	2.255***
			(32.01)	(6.24)
Branches			-1.761	
			(-0.93)	
GNI			-0.080***	0.188
			(-4.96)	(1.34)
Population			13.631*	
			(1.80)	
Exchange rate			-0.015	0.020
			(-1.24)	(0.17)
_cons	58.243***	62.867***	75.385***	71.966***
	(40.70)	(35.92)	(34.91)	(5.65)
Bank-fixed	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes
N	4231	4231	4231	991
R-sq	0.322	0.326	0.569	0.753

*Notes: Estimated with a fixed-effects model, Table 4.8 presents the relationship between individual efficiency convergence and intangible assets. The t statistics are reported in parentheses. The present study uses an analyzing power of 10%, which means the null hypothesis will be rejected if the t value in the critical region is 5% for each side. *, **, *** are designated for the level of significance of 10%, 5% and 1%, respectively. The dependent variable is individual efficiency difference. The main explanatory variable in our regression is the interaction term of the initial level (L. Individual efficiency) and intangible assets (Intangibles). We control the bank and country-specific factors in column (3) and the Fintech development level (Fintech score) in columns (4).*

Table 4.9 The relationship between intangible assets and meta-efficiency convergence

Dependent variables	Meta-efficiency difference			
	(1) Fixed effects	(2) Fixed effects	(3) Fixed effects	(4) Fixed effects
L. Meta-efficiency	-0.654***	-0.602***	-0.625***	-1.402***
	(-41.99)	(-34.96)	(-37.68)	(-12.59)
Intangibles		27.750***	28.923***	43.386***
		(7.16)	(7.79)	(3.49)
L. Meta-efficiency * Intangibles		-0.291***	-0.299***	-0.454***
		(-7.08)	(-7.60)	(-3.40)
Fintech score				-12.011***
				(-2.62)
L. Meta-efficiency * Fintech score				0.129***
				(2.80)
NPLR			0.163***	0.071
			(8.45)	(1.20)
EA			0.080***	-0.028
			(2.96)	(-0.31)
IIR			0.016***	0.035***
			(3.32)	(2.80)
ROA			1.200***	1.590***
			(15.75)	(7.85)
Branches			-5.610***	
			(-3.75)	
GNI			-0.026**	-0.018
			(-2.04)	(-0.18)
Population			3.660	
			(0.61)	
Exchange rate			0.008	0.031
			(0.85)	(0.40)
_cons	60.555***	55.615***	56.079***	125.960***
	(42.10)	(34.99)	(28.24)	(13.73)
Bank-fixed	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes
N	4231	4231	4231	991
R-sq	0.342	0.352	0.409	0.647

*Notes: Estimated with a fixed-effects model, Table 4.9 presents the relationship between meta-efficiency convergence and intangible assets. The t statistics are reported in parentheses. The present study uses an analyzing power of 10%, which means the null hypothesis will be rejected if the t value in the critical region is 5% for each side. *, **, *** are designated for the level of significance of 10%, 5% and 1%, respectively. The dependent variable is meta-efficiency difference. The main explanatory variable in our regression is the interaction term of the initial level (L. Meta-efficiency) and intangible assets (Intangibles). We control the bank and country-specific factors in column (3) and the Fintech development level (Fintech score) in columns (4).*

Table 4.10 The relationship between intangible assets and total efficiency convergence

Dependent variables	Total efficiency difference			
	(1) Fixed effects	(2) Fixed effects	(3) Fixed effects	(4) Fixed effects
L. Total efficiency	-0.007***	-0.007***	-0.007***	-0.012***
	(-39.52)	(-32.48)	(-36.78)	(-6.85)
Intangibles		0.044	0.083*	0.487**
		(0.96)	(1.92)	(2.50)
L. Total efficiency * Intangibles		-0.000	-0.001*	-0.006***
		(-0.73)	(-1.68)	(-2.94)
Fintech score				0.021
				(0.37)
L. Total efficiency * Fintech score				-0.000
				(-0.61)
NPLR			-0.002***	-0.006***
			(-3.45)	(-2.73)
EA			0.002**	0.008**
			(2.08)	(2.30)
IIR			0.001***	0.001***
			(4.62)	(2.60)
ROA			0.038***	0.037***
			(18.27)	(4.95)
Branches			-0.184***	
			(-4.50)	
GNI			-0.002***	0.001
			(-4.93)	(0.43)
Population			0.034	
			(0.21)	
Exchange rate			0.000	-0.001
			(1.14)	(-0.30)
_cons	60.555***	55.615***	56.079***	125.960***
	(42.10)	(34.99)	(28.24)	(13.73)
Bank-fixed	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes
N	4231	4231	4231	991
R-sq	0.312	0.312	0.402	0.615

*Notes: Estimated with a fixed-effects model, Table 4.10 presents the relationship between total efficiency convergence and intangible assets. The t statistics are reported in parentheses. The present study uses an analyzing power of 10%, which means the null hypothesis will be rejected if the t value in the critical region is 5% for each side. *, **, *** are designated for the level of significance of 10%, 5% and 1%, respectively. The dependent variable is total efficiency difference. The main explanatory variable in our regression is the interaction term of the initial level (L. Total efficiency) and intangible assets (Intangibles). We control the bank and country-specific factors in column (3) and the Fintech development level (Fintech score) in columns (4).*

Appendix 4.1

Table A4.1 Definitions of variables for estimating cost function.

Panel A: Outputs	
Total loans ratio ($Loans$)	The ratio of interest-earning assets (the major element of which is loans) to total assets. The interest-earning assets consist of loans and advances to banks and customers, reverse repos, securities borrowed and cash collateral, as well as held-to-maturity financial assets. $$Loans = \frac{\text{Interest earning assets}}{Total\ assets} * 100$$
Other earning assets ($Other\_Earnings$)	The ratio of other earning assets to total assets. Other earning assets consist of derivative financial instruments, available for sale, trading at fair value, investment property, investments in associated companies, brokerage receivables, and insurance assets. $$Other\_Earnings = \frac{Other\ earning\ assets}{Total\ assets} * 100$$
Panel B: Inputs	
Human capital price ($Labor$)	The ratio of overheads (the major element of which is normally salaries) to total assets net of fixed assets. $$Labor = \frac{Overheads}{Total\ assets - Fixed\ assets} * 100$$
Physical capital price ($Physical$)	The ratio of non-interest expenses net of overheads to fixed assets. $$Physical = \frac{Non\ interest\ expenses - Overheads + Provisions}{Fixed\ assets} * 100$$
Funding price ($Funding$)	The ratio of interest expenses to total deposits and short-term funding. $$Funding = \frac{Interest\ expenses}{Total\ deposits + Short\ term\ funding} * 100$$
Panel C: Total cost	
Total cost ($Cost$)	The sum of three types of input cost in Panel B.

Table A4.2 Definition of variables for estimating efficiency.

Panel A: Bank-specific factors	
Ownership ($Listed$)	A dummy variable which is 1 for publicly listed bank, and 0 otherwise.
Non-performing loans ratio ($NPLs$)	The ratio of non-performing loans to total loans. A measure of doubtful loans. $$NPLR = \frac{Impaired\ loans}{Loans + Loan\ loss\ reserve} * 100$$
Capital ratio (EA)	The ratio of equity to total assets. A measure of cushion, the equity invested in the bank, against asset malfunction. $$EA = \frac{Equity}{Total\ assets} * 100$$
Interest income ratio (IIR)	The ratio of net interest revenue to operating income. $$IIR = \frac{Net\ interest\ revenue}{Operating\ income} * 100$$
Profitability (ROA)	The ratio of profit before tax to average assets. A measure of banking profitability. $$ROA = \frac{Profit\ before\ tax}{Average\ assets} * 100$$

(Continued on the next page)

Table A4.2 Continued

Panel B: Country-specific factors	
Population density (Population)	Population density is midyear population (in thousand) divided by land area in square kilometers. The population counts all residents regardless of legal status or citizenship - except for refugees not permanently settled in the country of asylum. Land area is a country's total area, excluding areas under inland water bodies, national claims to continental shelves, and exclusive economic zones.
Per capital income (GNI)	GNI per capita (in thousands of U.S. dollars) is the gross national income, converted to U.S. dollars using the World Bank Atlas method, divided by the midyear population. GNI is the sum of value added by all resident producers plus any product taxes (less subsidies) not included in the valuation of output plus net receipts of primary income (compensation of employees and property income) from abroad.
Number of banking branches (Branches)	Commercial bank branches are retail locations of resident commercial banks and other resident banks that function as commercial banks that provide financial services to customers and are physically separated from the main office but not organized as legally separated subsidiaries.
Exchange rate (Exchange)	The official exchange rate is the rate set by a country's governing authorities or established in the legally authorized exchange market. This rate is computed as an annual average, derived from monthly averages that express the value of the local currency in relation to the U.S. dollar.

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Table A4.2 Continued

Panel C: Technology factor	
Intangible assets ($Intangibles$)	Intangibles represents a bank's other intangible assets, the major element of which is software and patents, and excludes goodwill.
Alternative intangible assets ($Intangibles\_pred$)	There may be land use rights existing in the bank's intangible assets. To assess a more accurate value of technological assets, we adopt the positive values of the residuals in a regression model that regress other intangible assets to total assets in the robustness test because land use rights may be related to banks' size and total assets, while technological assets, especially new patents of small and medium banks that are struggling to survive with Fintech innovation, maybe not very associated with their total assets. $$Intangibles_{ijt} = \alpha_0 + \beta_1 Total\ assets_{ijt} + \epsilon_{ijt}$$
Global Fintech Index ($Fintech\ score$)	Country-level Global Fintech Index for Fintech ecosystem quality is published by Findexable. The higher the score, the more advanced the Fintech in that country. The original Fintech score index is transformed into nature logarithms as follows. We use the residues of Fintech after regressing on GNI to eliminate the multicollinearity problem. $$Fintech\ score = \log\left(Global\ Fintech\ score\ index + 1\right)$$

(Continued on the next page)

Table A4.2 Continued

Panel D: Competitiveness	
Lerner index ($Lerner\ index$)	The Lerner index is measured as the percentage of price over marginal cost. P is the price of banking total output. We measure P by the ratio of banking revenues to total assets while banking revenues are composed of interest income and non-interest income. MC is the marginal cost for banking output. We proxy MC by the ratio of the total cost to banking revenues. $$Lerner = \frac{P - MC}{P}$$
Alternative Lerner index ($Lerner\ index\ of\ total\ loans$)	This is a stochastic Lerner index with respect to total loans that is calculated as formula (13) to (18) in Appendix.
Alternative Lerner index ($Lerner\ index\ of$ $other\ earnings\ assets$)	This is a stochastic Lerner index with respect to other earning assets that is calculated as formula (13) to (18) in Appendix.

Table A4.3 Sample and observations.

Country and region	Observations	Banks
European Union (EU): Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovak Republic, Slovenia, Spain, Sweden	2175	268
United States (US)	1377	156
Japan (JP)	938	113
Mainland China (CN)	787	87
Total number	5277	624

Notes: Data from commercial banks was collected from 30 countries over a 10-year period from 2012 to 2021. Data from the United Kingdom of Great Britain and Northern Ireland (UK), Canada (CA), Australia (AU), and other countries were excluded because of the missing value problem and convergence problem. Data from the United States (US) was drawn from the database with random sampling to eliminate bias when estimating with macro factors.

Table A4.4 Variance inflation factor

Panel A			Panel B		
Variable	VIF	1/VIF	Variable	VIF	1/VIF
Intangibles	1.190	0.840	Intangibles	1.260	0.793
Listed	1.150	0.871	Listed	1.210	0.825
NPLR	1.660	0.601	NPLR	1.550	0.645
EA	1.520	0.659	EA	1.760	0.569
IIR	1.430	0.701	IIR	1.580	0.635
ROA	3.260	0.307	ROA	3.510	0.285
Branches	1.450	0.691	Branches	1.490	0.672
GNI	1.560	0.639	GNI	1.840	0.543
Population	1.400	0.712	Population	1.440	0.693
Exchange rate	1.350	0.738	Exchange rate	1.470	0.679
Lerner index	2.920	0.342	Lerner index	2.810	0.356
			Fintech score	1.690	0.592
Mean VIF	1.720		Mean VIF	1.800	

Notes: Variance inflation factor (VIF) is the ratio of the overall variance in a multiple regression model to the variance of a model that includes only one single independent variable in the above multiple regression. A higher VIF for a variable indicates a high degree of linear relationship to other regressors. VIF in Panel A is calculated to identify multicollinearity when estimated with Intangibles. VIF in Panel B is calculated to identify multicollinearity when estimated with Intangibles while controlling national Fintech development (Fintech score). We separately examine the multicollinearity because controlling Fintech development restricted our sample in 2020 and 2021. In the present study, a VIF above 5 indicates high multicollinearities. Presented VIF and 1/VIF in Table A4 show no existence of high multicollinearities.

Table A4.5 Banks' individual efficiency and meta-efficiency

		Individual efficiency	Meta-efficiency	Total efficiency
EU	Mean	0.881	0.943	0.857
	Std.dev.	0.069	0.045	0.126
US	Mean	0.965	0.970	0.912
	Std.dev.	0.045	0.005	0.076
JP	Mean	0.934	0.966	0.912
	Std.dev.	0.064	0.011	0.071
CN	Mean	0.948	0.753	0.837
	Std.dev.	0.051	0.067	0.062

Notes: Banks efficiencies are produced via $e^{-E(U|\varepsilon)}$. U_{ijt} *estimated in the first step represents banks' individual inefficiency which is determined by banking-specific factors like non-performing loan ratio (NPLs), capital ratio (EA), profitability (ROA), ownership (Listed), while* U_{ijt}^{M} *estimated in the second step is interpreted as meta-inefficiency which result from national environmental and regulatory factors like population density (Population), GNI per capita (GNI), and the number of banking branches (Branches). We winsorized the values beyond the limits of 1% and 99%.*

Appendix 4.2 A stochastic approach of measure competitiveness

Instead of approximating a firm's marginal costs using the ratio of average costs, banks' marginal costs in the Lerner index can be calculated from a trans-log cost function (Coccorese, 2014). Setting price P_{it} higher than or equal to marginal cost MC_{it}, a profit-maximizing behavior is represented as formula (A1). We rewrite formula (A1) into (A2) and (A2'), which denotes the ratio of revenue share to total costs for bank i at time t in one country is higher than or equal to the cost elasticity with respect to output Y_{it}. The ratio of revenue share to total costs (RC_{it}) is interpreted as a stochastic cost frontier (formula A3) and rewritten in formulas (A4) and (A5). Thus, we calculate the stochastic Lerner index concerning total loans and other earning assets through the formula (A6).

$$P_{ijt} \geq MC_{ijt} \tag{A1}$$

$$\frac{P_{ijt}Y_{ijt}}{TC_{ijt}} \geq \frac{\partial TC_{ijt}Y_{ijt}}{\partial Y_{ijt}TC_{ijt}} \tag{A2}$$

$$\frac{TR_{ijt}}{TC_{ijt}} \geq \frac{\partial lnTC_{ijt}}{\partial lnY_{ijt}} \tag{A2'}$$

$$RC_{ijt} = \frac{\partial lnTC_{ijt}}{\partial lnY_{ijt}} + u_{ijt} + v_{ijt} \tag{A3}$$

$$\frac{P_{ijt}Y_{ijt}}{TC_{ijt}}\frac{\partial lnY_{ijt}}{\partial lnTC_{ijt}} - 1 = u_{ijt}\frac{\partial lnTC_{ijt}}{\partial lnY_{ijt}} \tag{A4}$$

$$\frac{P_{ijt}-MC_{jit}}{MC_{ijt}} = \theta_{ijt} = \frac{u_{ijt}}{\frac{\partial lnTC_{ijt}}{\partial lnY_{ijt}}} \tag{A5}$$

$$Lerner\ index_{ijt} = \frac{\theta_{ijt}}{1+\theta_{ijt}} \tag{A6}$$

5 Conclusions, implications, and limitations

In a context where technological innovations challenge the dominant position of traditional commercial banks, this study empirically examines the impact of digital payment platforms on the profitability and risk-taking behaviors within the Chinese banking sector. The results reveal a notably adverse effect of digital payment platforms on the risk-taking behaviors of Chinese commercial banks, a finding robust across different explanatory variables. Additionally, the study indicates an adverse impact of digital payment platforms on the profitability of urban and rural commercial banks. This suggests a developmental disadvantage for urban and rural commercial banks, although this result is not very robust. We also found that as the country issued and implemented an array of regulatory policies and due to COVID-19, the negative effect turned to a positive effect on profitability, and the inhibitory impact on risk-taking became more notable.

Against this background that the ever-increasing use of financial technologies, is posing a challenge to the profitability of the traditional financial industry and influencing risk management, incumbent commercial banks are reacting as an array of corporations. Subsequently, the study explores whether banks' involvement in technology, such as technology-driven M&A transactions, affects their opacity in Japanese context. The findings provide evidence that technology-driven M&A transactions are negatively associated with bank opacity, a result consistent across various econometric techniques and different treatment variables. Furthermore, the study observes that the attenuation effect is more pronounced for foreign technology-driven M&A transactions. Considering that bank opacity is inversely related to stock price informativeness, this study additionally investigates the impact of technology-driven M&A transactions on stock price synchronicity and risk composition. Estimated results indicate that banks participating in technology-driven M&A transactions experience reduced stock price synchronicity and systematic risk.

The acquisition of software and technological products through M&As and purchases serves as a pathway for adopting digital transformations, with the acquired assets recorded as intangible assets, an opaque asset that captures the synergy arising from M&As while bearing predictive significance for the long-term success of business combinations, on the balance sheet. This study provides empirical evidence for the relationship between bank efficiency and identifiable intangibles, primarily consisting of software after excluding goodwill. Findings suggest that intangible assets enhance a bank's efficiency, with a more pronounced fostering effect on improving meta-efficiency. Moreover, considering varying competition or cooperation and differentiation among incumbent commercial banks resulting from the level of national fintech development, intangible assets play a crucial role in fostering perfect competition and accelerating the convergence of efficiency.

The implications of our findings carry practical significance in the economic landscape. First, when considering the broader landscape, our study holds substantial value for countries at various stages of financial technology development. Our study implies that the dynamics between traditional financial institutions and emerging financial technologies, as well as the overall progress of these industries, hinge on the approach and willingness of both banks and financial technology companies to collaborate (Brandl and Hornuf, 2020; Temelkov, 2018), as well as the regulatory changes they adopt. Banks have the option to forge a robust collaboration with financial technology, which yields benefits such as reduced capital expenditure for risk management through big data utilization, expanded access to younger demographics and geographically distant customers. Financial technology companies in turn gain from leveraging the established brand reputation and extensive customer base of banks. Moreover, rural commercial banks or those in developing regions may find themselves at a disadvantage compared to counterparts engaged in strategic collaborations, necessitating additional governmental support. Notably, collaboration with financial technology companies has the potential to alleviate the higher non-performing loan ratio characteristic of rural commercial banks.

Second, opacity in financial markets, as highlighted in prior study, poses a threat to information efficiency, resulting in increased price synchronicity and heightened susceptibility to systemic market failure (Jones et al., 2012). While playing a role in facilitating digital transformation, technology engagement also shows promise in mitigating vulnerability to systemic market failure through reduced opacity of banks, decreased systematic risk in stocks, and lower stock price synchronicity. Ultimately, this contributes to enhanced stability in the stock market.

Third, despite the tendency of larger and publicly listed banks to offer detailed disclosure of intangible assets, a significant number of banks still fall short in providing comprehensive reports. In the contemporary landscape that is increasingly shaped by technology and research, it is imperative to adopt a more detailed approach to accounting disclosure. Much like M&As and R&Ds, intangible assets on the balance sheet serve as indicators of organizational strategies. Therefore, a more comprehensive approach to accounting disclosure becomes instrumental in fortifying external oversight and facilitating accurate evaluations.

Finally, the present study has several limitations. First, our research is limited by a lack of common standards and sufficient data for measuring the development of financial technologies. Second, it is crucial to acknowledge and address the associated risks of collaboration, including cybersecurity issues, regulatory challenges, and potential power outages. Third, while technology-driven M&As reduce vulnerability to systemic market failure, we must acknowledge the technology-triggered riskiness, given the inherent riskiness of the high-tech industry and the increasingly close relationship between incumbent banks and technology companies. Last, further analysis is essential. For example, the influencing mechanisms through which technology-driven mergers M&As reduce bank opacity remain ambiguous. We hypothesize that there might be channels involving knowledge synergy and risk diversification, but further research is necessary to explore these aspects. We employed a two-stage analysis method that estimates efficiency first and examines its relationship with intangibles second to assess the impact of intangible assets. One reason for this approach is to control for banks' competitive ability while addressing endogeneity concerns. Further research could explore simultaneous estimation approaches and integrate steps 3 and 4 into steps 1 and 2. Various methods, such as different models of SFA and DEA, can be employed to evaluate bank efficiency to generate accurate and robust conclusions.

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