# ***Banks' Shadow Activities and Fintech Adoption: Implications for Complexities, Risk Exposure, and the Cost of Debt***

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# Abstract

This thesis explores the prevailing trends of banks' shadow activities and Fintech adoption, examining their combined influences on risk management and borrowing firms. As the landscape of shadow banking evolves and rapid advancements in Fintech continue, the banking sector faces both opportunities and challenges. This research assesses how banks' utilization of both shadow activities and Fintech innovations impacts their risk exposure and broader economic implications.

The first study analyzes the risk profiles associated with banks' shadow activities, highlighting how the complexity of banks' business and organizational structures can exacerbate vulnerabilities, despite initial reductions in risk through off-balance-sheet exposures. The second study examines the interplay between Fintech adoption and banks' shadow activities, demonstrating that technological innovations can simultaneously lower risk while also increasing it when combined with shadow banking. The third study assesses the impact of Fintech on the cost of bank debt for borrowing firms, revealing that technological advancements reduce information asymmetries, thereby benefiting these firms by lowering their borrowing costs.

Ultimately, this thesis contributes to existing literature by providing comprehensive insights into the dual dynamics of shadow banking and Fintech. It underscores the need for effective regulatory frameworks that balance the innovative trends in the banking industry with stability and encourages a rethinking of the future role of traditional banks in the financial system.

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# Chapter 1
# General Introduction

## 1. 1. Background and Motivation

The banking industry has long been the cornerstone of the global financial system, playing a crucial role in facilitating economic growth and maintaining stability. Traditionally, banks have served as vital intermediaries in the financial markets, providing essential services such as accepting deposits, extending loans, and facilitating payments. Their ability to assess credit risk and allocate capital effectively has been fundamental to the functioning of economies worldwide. However, the role of banks is currently being reshaped by two decentralized shifts in the financial landscape.

First, the emergence of shadow banking—a system of credit intermediation occurring outside the traditional banking sector—has introduced new dynamics and complexities, challenging existing regulatory frameworks and traditional financial practices. Second, the rapid advancement of financial technology (Fintech) is transforming the way finance is conducted, offering innovative solutions that enhance efficiency and improve customer experiences. In response to these developments, banks are evolving their behaviors and strategies, leading to the growth of banks' shadow activities and the integration of Fintech solutions. Understanding these transformations—particularly their impact—is crucial for navigating the future of banking and forms the core focus of this thesis.

Shadow banking refers to credit intermediation activities that operate outside the regulatory framework, encompassing entities and activities similar to those found in traditional banking (FSB, 2012). As early as the 1970s, Minsky (1986), observing the effect of asset securitization and non-bank financial institutions in amplifying credit cycles and creating financial chaos for the whole credit market, defines these intermediaries as fringe banking since they are outside regulatory supervision.

Banks' shadow activities involve the creation of off-balance-sheet entities outside the formal banking system, which rely on uninsured wholesale funding in various ways to finance their operations. One significant aspect of banks' engagement in shadow banking lies in their capacity to circumvent conventional lending constraints. For example, when a bank reaches its lending limit for a particular industry or borrower, it may issue debt securities, such as wealth management products or commercial paper, to investors in exchange for cash. This cash is subsequently entrusted to a trust fund or another financial intermediary, which then lends the funds to the actual borrowers. In this arrangement, the debt securities issued by the bank are not classified as 'bank deposits,' and the investments made through the intermediary are not considered 'bank loans.' Consequently, the bank can extend additional loans without technically exceeding its lending limit and evading regulatory oversight. While the securities issued by banks are generally viewed as low-risk and high-quality, there remains a possibility of default, which could lead to a credit crunch (Pagano & Volpin, 2012).

Banks may create off-balance-sheet entities by forming special purpose vehicles (SPVs). These entities' function are shell companies controlled by banks, enabling them to transfer assets off their balance sheets in order to circumvent capital requirements and reduce bankruptcy costs. For instance, when a bank holds a substantial portfolio of mortgages, it may create an SPV to which these loans are transferred. This process allows banks to obscure debts and decrease the amount of securitized assets on their balance sheets, effectively lowering their risk-weighted assets. As a result, banks can reduce the capital they are required to hold without altering their underlying risk exposure. This mechanism enables banks to sell more securities backed by the transferred loans to investors, thereby raising additional capital without the need to issue new equity or debt. Moreover, SPVs are not necessarily consolidated into the banks' financial statements and are subject to their own set of regulations, which may be less stringent than those governing banks. However, banks are not completely insulated from liability. During the 2008 financial crisis, when these shell companies encounter difficulties, sponsoring banks often intervene to provide guarantees due to reputational concerns. Consequently, the impaired assets held by the SPVs may eventually return to the banks' balance sheets, increasing their risk exposure and contributing to systemic risk within the financial system (Adrian & Ashcraft, 2012; Gorton & Souleles, 2007).

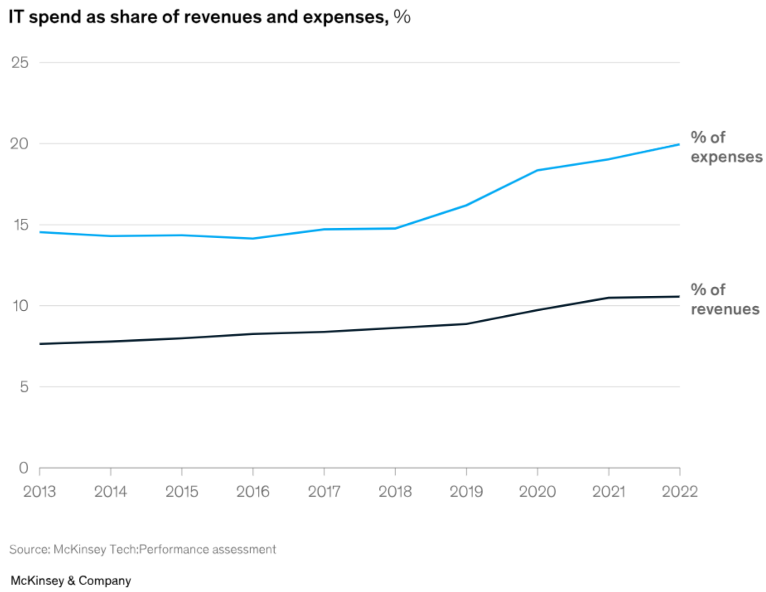
Furthermore, banks may engage in shadow banking activities by actively trading or holding securities, such as mortgage-backed securities (MBS) or government bonds, for investment purposes. These securities can be used as collateral to secure funding through repurchase (repo) transactions or other forms of securities lending, which allow banks to access funds beyond traditional deposits and expand their lending capacity. However, these activities introduce certain risks. For instance, if the value of the securities held as collateral declines, the bank may be required to provide additional collateral or face a margin call, which could lead to a shortfall in liquidity. Typically, these securities are categorized as investment securities held either for trading purposes or until maturity. Investment securities held for trading are classified as available-for-sale (AFS) securities, while those intended to be held to maturity are designated as held-to-maturity (HTM) securities. According to accounting standards, the revaluation of the fair value of AFS and HTM securities is not reflected on the profit and loss statement. Instead, they are recognized as unrealized gains or losses within the other comprehensive income statement or may remain unrecognized (IFRS, 2025). As a result, banks may face potential losses that are not immediately visible to investors or regulators. Some may argue that the unrealized losses associated with AFS and HTM securities are not 'real' losses because they do not impact on the financial statements in the books. However, in the event that a bank experiences a liquidity crisis and needs to liquidate these securities, there could be significant risk exposure, underscoring the importance of transparency and accurate risk assessment in banking operations during the 2008 financial crisis (Loutskina, 2011; Uzun & Webb, 2007).

Recent studies have revealed other new ways of shadow banking activities conducted by banks. Chang, Yang, and Shi (2022) propose that banks strategically utilize their affiliated leasing firms to bypass government-imposed credit-tightening policies that specifically aim to restrict lending to industries experiencing overcapacity. In other words, when the government enforces measures to limit credit availability to industries facing issues of excessive production capacity, banks find ways to work around these restrictions by using their affiliated leasing firms instead of extending traditional loans. Specifically, they find that compared to non-bank affiliate leasing firms, bank affiliate leasing firms increase finance leases to companies that were subject to the targeted credit tightening policy.

Over the last few decades, a growing body of literature has highlighted the significant impact of banks' shadow activities on financial stability and risk. Researchers such as Hassan, Karels, and Peterson (1993) examine the relationship between bank risk levels and various forms of off-balance-sheet (OBS) exposures, including loan commitments and commercial letters of credit. Similarly, Jagtiani and Khanthavit (1996) conduct an aggregated analysis of OBS exposures, assessing their overall risk-weighted sum. Additionally, An and Yu (2018) explore the drivers and effects of guaranteed OBS business within Chinese commercial banks through the lens of Desirability Lending Policy (DLP), finding a reciprocal influence between commercial loans and OBS business activities. Zhang, Chen, and Jin (2020) further contribute to this dialogue by investigating the effect of new asset management regulations on banks' OBS innovations and risk-taking behaviors, utilizing unbalanced panel data from 75 commercial banks in China over a decade. Haq, Tripe, and Seth (2022) examine the connection between OBS activities and bank risk in publicly traded commercial banks across the G-7 nations, revealing a non-linear relationship between these variables.

In general, while there is growing insight into how banks engage in shadow banking activities, the exact scope, definitions, and overall extent of these operations remain ambiguous and continue to evolve. This ambiguity complicates efforts to accurately assess their overall impacts, making it challenging for regulators, researchers, and market participants to identify and manage the associated risks. Consequently, this lack of clarity can lead to regulatory gaps and increased financial instability, particularly in relation to bank risk management. Moreover, these shadow activities are closely intertwined with both organizational and business complexity and can twist a bank's risk exposure.

The rise of financial technology (Fintech) introduces additional dimensions that challenge our understanding of the traditional banking industry. Fintech represents a technology-driven financial innovation encompassing a wide array of advancements designed to disrupt and enhance various financial activities. It leverages technological innovations, including software, applications, algorithms, and data analytics, to provide novel solutions that improve user experiences, reduce operational costs, and increase accessibility to financial services. In recent years, the global banking sector has seen a significant rise in IT investments as banks prioritize building their in-house digital capabilities rather than simply outsourcing expenditures. As shown in Figure 1.1, banks allocate between 6% and 12% of their revenue to IT spending, which accounts for 15% to 20% of their total operating expenses—a substantial portion compared to other major industries (Patenge, Anand & Goel, 2024).




Source: https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/tech-forward/managing-bank-it-spending-five-questions-for-tech-leaders

Figure 1.1: IT spend as share of revenues and expenses

FinTech has driven technical innovations within the banking industry, altering how banks operate. Banks have digitalized and automatized their operations and customer service by integrating a variety of fintech applications and advanced technologies. For example, through digital platforms and mobile applications, banks provide customers with real-time access to banking services, enhancing convenience and engagement. Robo-advisors offer personalized financial advice, improving customer service and operational efficiency. Behind the scenes, powerful computing capabilities, combined with AI, big data, and blockchain, revolutionize data handling—from creation and storage to analysis and sharing. This technological integration allows banks to process and exchange data while also offering the scalability and flexibility needed to adapt to changing financial demands. Moreover, the influence of Fintech extends beyond technology, reshaping banks' mindsets, business models, and strategic approaches. It allows banks to establish intelligent, data-driven decision-support systems, aiding in the formulation of optimal business strategies and enhancing operational performance (Elsaid, 2023; Guerra & Castelli, 2021; Siek & Sutanto, 2019).

While Fintech offers significant benefits to the banking industry, the extent of its impact and future development trends remain subjects of ongoing debate. Especially, there is an inconclusive understanding of the impact of banks' Fintech adoption on their risk. On the one hand, the initial investments and substantial expenses associated with building Fintech infrastructure can drive up operational costs and erode profits, elevating the risk of defaults. The competitive landscape shaped by high-tech giants' pressures banks to engage in costly innovations, which can further decrease profits and encourage riskier behaviors. Additionally, the integration of new technologies into Fintech introduces cybersecurity threats, such as cyberattacks and data breaches, which can lead to potential bank defaults and vulnerabilities.

On the other hand, Fintech facilitates risk management and reduces related costs by enhancing their ability to analyze and manage risks effectively. For instance, banks use machine learning to automate data analysis and risk assessment tasks, enabling them to process vast amounts of information quickly and objectively. These AI algorithms can identify patterns in customer behaviors, transaction data and digital interactions, helping banks detect fraudulent activities and assess credit risks more accurately. Additionally, Fintech provides predictive insights into regulatory trends and customer preferences, allowing banks to proactively manage potential risks and strengthen compliance with regulatory requirements.

In addition, questions such as how and to what extent banks' adoption of Fintech influences their corporate clients remain underexplored. Specifically, how banks' Fintech adoption influences the cost of debt for their corporate clients remains largely unknown. This occurs when Fintech reduces information asymmetries between borrowers and lenders, thereby lowering the expenses associated with pre-loan screening and post-loan monitoring. As a result, banks may lower premiums initially charged to cover unobservable risks, thereby decreasing the cost of debt for\borrowers.

However, it is also possible that Fintech adoption might result in a higher cost of bank debt for borrowers. This is because, when investing in Fintech, significant upfront expenses such as capital expenditure and training costs may occur, which may take years to recoup. To protect their financial stability from the potential negative consequences of these investments, banks need to channel and offset these costs. Among different ways of increasing revenue to cover such costs, charging higher interest rates on loans could be an immediate approach, consequently increasing the cost of debt for borrowing firms.

Overall, while the adoption of Fintech in the banking sector has been studied, significant gaps remain. First, there is a need for further empirical verification and generalization of how fintech affects banks' risk management. Second, the interaction between fintech and traditional banking practices requires deeper exploration. Finally, understanding the impact of fintech on firms is crucial, as it influences business operations and strategies within the financial landscape.

## 1. 2. Thesis Structure

The objective of this thesis is to construct a research framework for exploring the evolution of shadow banking and FinTech adoption in the banking industry. By analyzing empirical applications, this study aims to investigate how banks' interplay with Fintech and shadow banking activities influences traditional banking practices. This thesis contains 5 chapters. Chapter 1 is a general introduction. Chapters 2, 3 and 4 display empirical applications. The final Chapter 5 presents a summary along with limitations of the study and improvements future work. The overall structure of the article is illustrated in Figure 1.2 below.

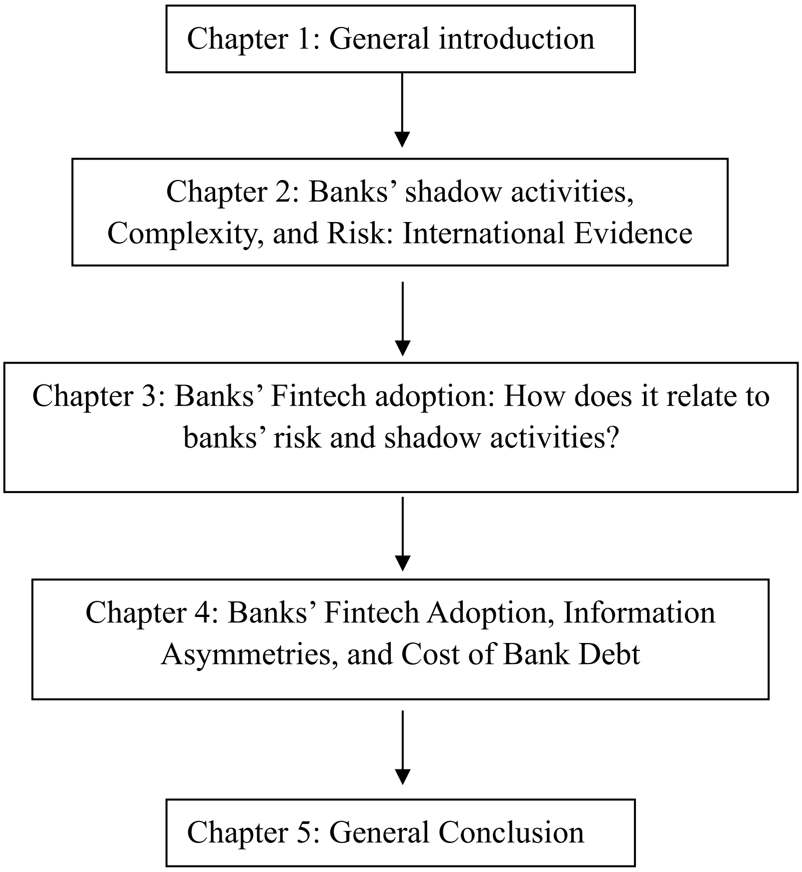



Figure 1.2: Overview of the thesis structure

Chapter 2 focuses on examining the relationship between banks' shadow activities and bank risk, while also exploring how bank complexities moderate this relationship. The analysis unfolds in several steps. Initially, I assess the average correlation between banks' shadow activities and bank risk. Given that shadow banking activities often occur off the balance sheets of traditional banks, I use the ratio of off-balance sheet items to total on- and off-balance sheet exposures as a proxy for banks' shadow. This measure primarily reflects the nature of banks' shadow activities. For bank risk assessment, I focus on the natural logarithm of non-performing loans (ln(NPL)) and the impaired loan-to-equity ratio. To accurately determine the relationship between banks' shadow and realized risks, I control for a range of bank-level and macroeconomic variables, incorporating bank and year fixed effects. To address concerns about reverse causality, I employ propensity score matching with difference-in-differences (PSM-DIDs) as an alternative identification strategy, using the designation of global systemically important bank (G-SIB) as the treatment. Because GSIBs, due to their heightened regulatory oversight and systemic importance, exhibit distinct levels of involvement in shadow banking activities, using a GSIB dummy as the treatment variable allows us to effectively investigate the impact of these shadow activities on bank risk. I then enhance the panel regression model by introducing bank complexity as interaction terms. Drawing from existing literature, I consider two dimensions of bank complexity: business complexity and organizational complexity. Business complexity is represented by two proxies: the non-interest income ratio and the NIS/NIM ratio. These capture the complexity and uncertainty of non-banking activities, with the former including stable income streams from services like wealth management and the latter reflecting riskier activities tied to investment securities dealing. For organizational complexity, I use three proxies: the number of branches, the number of employees, and the number of acquisition events. These indicators demonstrate the dispersion of legal entities controlled by bank groups and the extent of their integrated community network. Moreover, I test how internal capital market and agency problems influence these relationships.

Chapter 3 examines the implications of Fintech for banks, focusing specifically on banks' shadow activities and risk management. The key explanatory variable in this study is "Fintech," which is difficult to measure as it is a term with no standard definition and clear boundaries. Many studies address this by developing a Fintech development index and using Ordinary Least Squares (OLS) regression for analysis. However, these indexes often capture only the technological aspects of Fintech in banks, overlooking the strategic and intentional factors of Fintech adoption that are harder to observe and measure. To address this, I propose using "Fintech 3.0" as a proxy measure and treatment variable. I employ a staggered Difference-in-Differences (DIDs) approach, a quasi-experimental design that helps establish causal relationships between

Fintech and its impact on banks' shadow banking activities and risk profiles. During the sample period, banks varied in their adoption of Fintech 3.0. The DIDs method estimates the treatment effect of Fintech by comparing changes over time between a treated group and a control group. This approach allows for the inclusion of unobserved impacts of Fintech. I manually retrieved the year when keywords like "Fintech" first appeared in the annual reports of selected bank groups. In relevant cases, I performed placebo tests to rule out the influence of other factors and conducted parallel trend tests to ensure the assumption of the analysis is satisfied. In additional analysis, I examine the empirical relationship between Fintech and banks' shadow activities, and explore how Fintech influences the relationship between these shadow activities and bank risk.

Chapter 4 investigates how the cost of debt for borrowing firms is influenced by the Fintech adoption of their lending banks. I measure this impact by constructing a bank-level Fintech index, which is distributed using a loan-weighted rate, resulting in the Firm-Bank Fintech Influence Score (FBFTIS). The cost of debt is defined by the interest spread rate—the difference between the average interest expense and the annual one-year loan prime rate. Control variables include firm size, total revenue, firm age, Tobin's Q, the price-to-book (PB) ratio, and the liquidity ratio, along with province-level macroeconomic indicators like GDP per capita and the Consumer Price Index (CPI). Province, year, and industry fixed effects are incorporated to account for variations. To address self-selection bias, I conduct a Heckman test and a difference-in-differences (DIDs) approach to tackle potential endogeneity. This is crucial, as banks with advanced Fintech capabilities might favor lower-risk firms, thus reducing the cost of debt. I also examine whether reduced adverse selection and moral hazard are plausible channels and explore the role of fixed assets and reduced operational costs of lending banks as alternative explanations for the decrease in the cost of debt due to Fintech adoption.

Overall, these empirical chapters illustrate a research framework of how both Fintech and banks' shadow activities interact to reshape banking practices, influence risk management, and impact lending costs, highlighting a multifaceted transformation within the financial sector. Chapter 2 explores the relationship between banks' shadow activities and bank risk and examines how these are moderated by bank complexities. This chapter sets the foundation for understanding how internal banking operations can be influenced by external innovations like Fintech. Chapter 3 expands on this by investigating how Fintech, particularly through the lens of Fintech 3.0, impacts banks' shadow activities and their risk management strategies. It looks at how Fintech adoption can reshape these activities and influence overall risk profiles, providing a broader context for digital transformation in banking. Chapter 4 shifts focus to the implications of bank's Fintech adoption on the cost of debt for borrowing firms. It analyzes how Fintech adoption by lending banks affects this cost, highlighting the practical effects of Fintech on the bank-firm relationship, particularly in lending practices and financial outcomes for borrowers.

## 1.3. Contribution

The contributions of this thesis are pivotal in addressing the critical interplay between technological advancements, risk management, and the evolving nature of banks' shadow activities within the financial sector. As the landscape of banking continues to transform under the pressures of digitalization and regulatory changes, understanding these dynamics is essential for both academics and practitioners alike. This research aims to unravel the complexities of how Fintech adoption influences borrowing costs and capital allocation, while also investigating the implications of banks' shadow practices on their risk management strategies. By integrating insights from multiple perspectives—namely Fintech's role, the complexities of bank operations, and the challenges posed by shadow banking—this thesis provides a comprehensive framework that sheds light on the contemporary issues that banks face. The following sections will articulate the key contributions in each empirical analysis that underpin this research, collectively enriching our understanding of modern banking challenges.

Chapter 2 contributes to the understanding of banks' shadow activities and their impact on risk management. Initially, it utilizes a comprehensive bank-year dataset that includes many of the world's largest bank groups. As the shadow banking system, predominantly driven by non-bank financial institutions, continues to expand, traditional banks encounter challenges in maintaining market share and profitability. In response, they often turn to adopting more shadowed financial approaches. Despite this trend, the current empirical literature provides limited insight into whether this shift benefits or harms banks, with significant divergence on the matter. This study seeks to offer more generalized evidence and insights into these dynamics. Additionally, this research bridges the gap in the literature between bank complexity and shadow activities—areas typically explored separately in previous studies. By examining how shadow activities, bank complexity, and risk-taking interact, the study reveals that the level of risk associated with shadow activities varies with the complexity of the bank. This adds valuable insights to the existing body of knowledge. Moreover, the study introduces an innovative measure for bank complexity: the ratio of net interest spread to net interest margin (NIS/NIM ratio). Unlike traditional measures that focus solely on realized and reported income, this ratio offers a more comprehensive assessment by including both realized and unrealized gains, such as revaluation surpluses of financial assets. This provides a fuller depiction of a bank's business operations and offers practical insights into the complexities banks face in a shadow banking context (Haq et al., 2022; Zhang & Malikov, 2022).

In Chapter 3, contributions are made to the understanding of the interplay between banks' shadow activities, Fintech, and bank risk, providing a deeper analysis of these elements within the evolving financial landscape. Firstly, the research offers a nuanced exploration of digitalization's impact on the banking sector, with a particular focus on "Fintech 3.0." By investigating this advanced stage of Fintech evolution—currently the most disruptive to traditional banking, this work distinguishes itself from prior studies that address earlier digitalization trends. Utilizing an innovative difference-in-differences (DID) model with Fintech as a signaling indicator, the research captures the profound, often unobservable transformations that Fintech brings, offering both historical and cross-sectional analyses that delve into its substantial impact beyond incremental changes. Moreover, this thesis contributes to the literature by examining the intricate relationship and causality between Fintech and bank risk amidst shadow banking activities. With shadow banking undergoing significant transformation, understanding these shifts is crucial for ensuring financial stability. Diverging from studies that examine Fintech's effects on banks' shadow activities outside the traditional banking framework, this research analyzes the evolving dynamics within traditional banks, emphasizing how Fintech alters the nature and scope of shadow banking, and the inherent risks involved. This examination not only provides immediate insights into current banking practices but also lays a foundation for future inquiries into the broader implications of Fintech, encompassing financial market stability and consumer protection. By integrating these insights, the thesis enhances our comprehension of the broader financial ecosystem and underscores the critical roles of digitalization and innovation in shaping future banking landscapes (Chen et al., 2015; Ha, 2022; Buchak et al., 2018; Zhang, Que, & Qin, 2023).

Chapter 4 makes contributions in several significant ways, particularly through the exploration of banks' Fintech adoption—a key component across our studies. First, it provides comprehensive evidence demonstrating that Fintech adoption, a critical facet of technological development, plays a pivotal role in reducing borrowing costs for firms. By expanding on existing research that links Fintech to enhanced efficiency in capital allocation and information transmission, this thesis delves into the specific impacts on bank loan pricing. These insights not only extend current understanding but also underscore the potential for technological advancements in banking to support broader economic goals. Furthermore, within the context of information asymmetry and the associated borrowing costs, this Chapter builds upon foundational studies of relationship banking and the role of financial intermediaries. It offers novel evidence regarding the conditions under which Fintech adoption mitigates information asymmetry, effectively lowering borrowing costs. This contribution is particularly relevant as it broadens the discussion beyond traditional spatial perspectives, highlighting mechanisms that benefit both debtholders and borrowers through enhanced information processing capabilities facilitated by Fintech. Lastly, this work enriches the understanding of the informational channels utilized through Fintech adoption, particularly in improving credit allocation accuracy and reducing bank debt costs. By integrating concepts such as data analytics and machine learning, it provides a nuanced exploration of how banks can predict future firm performance more accurately. This not only enhances the credit assessment process but also reinforces the broader thesis theme of technological impact on financial market dynamics (Avery, Bostic, & Samolyk, 1998; Berg, Burg, Gombović, & Puri, 2020; Bian, Wang, & Xie, 2023; Gopal & Schnabl, 2022; Kutzbach & Pogach, 2024).

# Chapter 2
# Banks' shadow activities, Complexity, and Risk: International Evidence

## 2.1. Introduction

In the wake of the 2008 global financial crisis, the hidden risks and uncertainties arising from regulatory arbitrage within the traditional banking system, referred to as banks' shadow activities, came to light, raising concerns about the potential consequences for financial stability. Discussions around shadow banking system have been focused on non-banking financial institutions (Buchak, Matvos, Piskorski, & Seru, 2018; Du, Li, & Wang, 2023; Kambhu, Stiroh, & Schuermann, 2007), while traditional banks also play an essential role as they are closely working with non-banks and actively engaging in shadow banking activities in the form of commitments, guarantees, market-related activities, and advisory or management functions. For example, banks have been actively exploring and creating innovative instruments, like Special Purpose Vehicles (SPVs), as intermediaries to participate in securitization issues and trading activities. To circumvent regulatory oversight, banks' shadow activities are concealed from the balance sheet and exist as off-balance sheet operations, which raise the debates on the relationship between banks' shadow activities and bank risk (Zhang & Malikov, 2022).

The relationship between banks' shadow activities and bank risk remains inconclusive. Some studies (e.g., Gennaioli, Shleifer, & Vishny, 2012; Plantin, 2015) posit a positive relationship, arguing that banks create new securities that obscure true risk levels, leading to excessive risk-taking. These activities are typically accompanied by higher leverage, which increases risk further. For instance, entrusted loans can boost equity returns but simultaneously increase equity risk. Similarly, securitizations contribute to higher insolvency, portfolio, and leverage risks, as well as increased volatility in return on assets (ROA). Conversely, other studies (e.g., Avery & Berger, 1991; Hassan &

Sackley, 1994) suggest a negative relationship, as banks' shadow activities can increase systematic risk while reducing idiosyncratic risk. These activities generate diversification benefits that help reduce overall risk and improve liquidity and funding for banks, enhancing their financial stability. Additionally, banks' shadow activities raise investors' concerns about moral hazard, prompting them to demand higher returns. In response, banks may reduce their risk-taking to lower investors' expectations (Gennaioli, Shleifer, & Vishny, 2012, 2013; Li & Lin, 2016; Plantin, 2015). Both theoretically and empirically, it remains challenging to clearly identify the predominant effects of banks' shadow activities on bank risks.

Meanwhile, as the banking industry evolves, traditional banks have transformed into complex conglomerates. This phenomenon, referred to as “bank complexity”, has attracted increasing attention from regulators, investors, and policymakers due to its potential implications for bank risk and the broader financial system (Cetorelli, McAndrews, & Traina, 2014; Correa & Goldberg, 2022). Bank complexity can be classified into two forms: business complexity and organizational complexity (Cetorelli & Goldberg, 2014; Cetorelli et al., 2014). First, banks have been engaging in multiple lines of business activities and involve various types of products and services, either banking or non-banking, making their business operations more complex. Secondly, banks span multiple countries, through many distinct legal entities and across a wide scope of geographies, making their organizational structures more complex. Recent years have seen a growing trend where large and complex banks emerge, promoting the formation of financial capital, pursuing more profit opportunities, and expanding competitive space. Nonetheless, constant vigilance is necessary, as demonstrated in the 2008/2009 global financial crisis, for which high bank complexity proved extremely problematic for bank risk management (Schmid & Walter, 2009).

Existing studies claim that more complex banks are exposed to higher levels of risk (e.g., Carbó Valverde & Rodríguez Fernández, 2007). Business complexity can lead to higher risk exposure as banks chase higher returns, engage in riskier lending, and participate in speculative activities like proprietary trading, which exposes them to significant liquidity risk. Additionally, regulatory uncertainties and compliance costs associated with complex business operations further exacerbate risk-taking behaviors (Carbó Valverde & Rodríguez Fernández, 2007; Christiansen & Pace, 1994; Freixas, Lóránth, & Morrison, 2007; Freixas & Santomero, 2002; Marinelli, Nobili, & Palazzo, 2022; Rochet, 2004; Santos, 2000). Organizational complexity, characterized by the multiplicity of legal entities and structures, creates management and monitoring difficulties, exacerbates agency problems and moral hazards, and leads to information loss, all of which contribute to higher risk levels (Buch, Koch, & Koetter, 2013; Deng & Elyasiani, 2008; Liberti & Mian, 2008; Siggelkow & Rivkin, 2005; Skrastins & Vig, 2019). However, the extent to which the interaction between bank complexity and shadow banking relates to bank risk remains underexplored.

This chapter has two main objectives. One objective is to fill the research gap by providing global evidence on the relationship between banks' shadow activities and bank risk. Most extant studies are based on bank groups from a limited number of countries—primarily the US, China, and European nations—and therefore may lack generalizability. Recent years see the banking sectors of developing countries increasingly suffering from the issue of banks' shadow activities while relatively few studies have taken them into account (Athari, Isayev, & Irani, 2024 ; Ghosh, Gonzalez del Mazo, & Ötker-Robe, 2012). This study uses a global sample of up to 359 of the largest bank groups from 2008 to 2021 across over 60 countries, among which both developed and developing countries take significant proportions. Such a global sample provides further evidence across varying economic conditions, regulatory frameworks, and financial market structures. The other objective is to disentangle the effect of bank complexities on the relationship between banks' shadow activities and bank risks. Prior empirical evidence highlights the heterogeneous effects, emphasizing factors such as effective regulation and governance (Martynova & Vogel, 2022; Wu & Shen, 2019). A better understanding of the interaction among banks' shadow activities, bank complexity, and bank risk under a global context is not only important to bank groups, but also to regulators worldwide, as complex banks engaged in shadow banking activities may pose spillover risks to other financial systems.

The analysis included several steps. First, I test the average correlation between banks' shadow activities and bank risk. As mentioned, shadow banking activities are often conducted off the balance sheets of traditional banks. Therefore, I use the ratio of off-balance items to total on- and off-balance sheet exposures as the proxy of banks' shadow activities. This measure primarily indicates the nature of banks' involvement in shadow banking activities. As for the bank risk measures, I focus on the natural logarithm of non-performance loan (ln(NPL)) and impaired loans to equity ratio. Furthermore, to pinpoint the relationship between banks' shadow activities and realized risks as precisely as possible, I control for a wide range of bank-level and macroeconomic variables, including bank and year fixed effects. To address concerns of reverse causality, I use PSM-DIDs as an alternative identification method.

To explore the effect of bank complexity on the relationship between banks' shadow activities and bank risk, I then extend the panel regression framework by introducing bank complexity through interaction terms. Learning from existing literature (e.g., Bratten, Causholli, & Omer, 2019; Cetorelli & Goldberg, 2014; Marinelli et al., 2022), I consider two dimensions of bank complexity measures – business complexity arising from the multiple non-ordinary business activities that bank groups engage in, and organizational complexity arising from controlling interests in a range of legal entities with a bloated structure. I create proxies for both dimensions. Business complexity is captured by two proxies: Non-interest income ratio and NIS/NIM ratio, as there are many non-banking activities in both ratios include many non-banking activities whose nature and payoff structure are complex and unknown to outsiders. The non-interest income ratio primarily includes fee-based income from services such as wealth management, advisory services, insurance, and brokerage. These activities tend to have a more stable income stream. The NIS/NIM ratio reflects riskier activities, particularly those related to investment securities dealing, which are subject to greater valuation volatility under market fluctuations. As for organizational complexity, I use three proxies: number of branches, number of employees, and number of acquisition events, as these proxies indicate the dispersion of legal entities controlled by bank groups, the size of their internal community network, and the extent to which they operate in an integrated manner.

This paper presents several key findings. Firstly, the findings indicate that a higher degree of banks' shadow activities is associated with reduced realized risk, as measured by the ln(NPL) and impaired loans to equity ratio. These findings are consistent with similar studies using regional samples (Basheer, Waemustafa, Hidthiir, & Hassan, 2021 Hassan, 2021; Beck, Demirgüç-Kunt, Laeven, & Maksimovic, 2006; Hassan, 1993). Secondly, the negative impact of banks' shadow activities on risk is weakened by business and organizational complexity. Specifically, banks with greater business and organizational complexity that engage in shadow banking activities are exposed to higher levels of risk. Lastly, the research finds that internal capital markets and effective management do not mitigate the moderating effects of bank complexity on the relationship between banks' shadow activities and bank risk.

This study makes two key contributions. First, it contributes to the extensive literature examining the implications of banks' shadow activities on bank risk management. By using a comprehensive bank-year dataset that includes the largest bank groups globally, this research provides more generalized evidence on the topic. As the shadow banking system - driven by non-bank financial institutions – continues to expand, traditional banks face challenges in competing for market share and maintaining profitability. In response, they often adopt a "regulatory arbitrage" strategy, moving towards a more shadowed financial approach. However, the current empirical literature has given limited attention on banks and displays significant divergence on whether this issue is beneficial or detrimental to banks themselves (Haq et al., 2022; Zhang & Malikov, 2022). This research aims to shed further light on the relationship between banks' shadow activities and risk management in a broader and more comprehensive context.

The second major contribution of this paper is to bridge the gap between the literature on bank complexity and banks' shadow activities. Previous studies (e.g., Zhang & Malikov, 2022) often discuss these concepts separately. By exploring the relationship between banks' shadow activities, bank complexity, and risk-taking, the present study reveals that the level of bank risk driven by banks' shadow activities varies across banks with different levels of complexity, adding valuable insights to the existing body of knowledge. Additionally, the paper introduces a novel measurement for bank complexity, namely, the ratio of net interest spread to net interest margin (NIS/NIM ratio). Unlike the widely used proxy measures for banks' business complexity, which solely capture realized and reported income, the NIS/NIM ratio offers a more comprehensive assessment. The measurement reflects both realized and unrealized gains, including revaluation surpluses of financial assets, thereby providing a reasonable depiction of the complexity of a bank's business operations.

The remainder of this report proceeds as follows. section 2 presents literature review and key hypotheses. And section 3 provides the designs of the research. Section 4 illustrates the main empirical findings. Section 5 concludes the paper.

## 2.2. Literature review and hypothesis development

Previous studies have identified various types of bank risks, including operational risk, leverage risk, interest rate risk, market risk, systematic risk, and idiosyncratic risk (Berger, Curti, Mihov, & Sedunov, 2022; Dell'Ariccia, Laeven, & Marquez, 2014 2014; Duan, El Ghoul, Guedhami, Li & Li, 2021; English, 2002; Fernholz & Koch, 2017; Jarrow, 2008; Varotto, 2011). Among these, banks' idiosyncratic risk has received significant attention and would be the focus in this chapter. Idiosyncratic risk from banks is defined as the risk that arises from the unique characteristics and individual risk factors of a specific bank (Bessler, Kurmann, & Nohel, 2015). One of the main reasons for the financial crisis was that the banking sector and other financial institutions can be excessive risk-taking, leading to credit and liquidity uncertainties. Given the critical role banks play in the real economy, financial distress within the banking system can trigger contagious effects, potentially causing regional, national, or international financial instability. Deposit insurance and the "too-big-to-fail" policy are often regarded as drivers of banks' idiosyncratic risk (Mishkin, 2006; Moch, 2018). Existing studies also discuss various sources of idiosyncratic risk, including bank size, shareholder composition, leverage, and the quality of board governance (Bhagat, Bolton, & Lu, 2015 ; Chen, Jeon, Wang, & Wu, 2015; García-Kuhnert, Marchica, & Mura, 2015; Sun & Liu, 2014). Over the past few decades, literature has explored the impact of banks' shadow activities on bank risk, particularly banks' idiosyncratic risk, with conclusions varying (An & Yu, 2018; Haq et al., 2022; Hassan et al., 1993; Jagtiani & Khanthavit, 1996; Zhang et al., 2020).

### 2.2.1. Banks' shadow activities and bank risk

Research on the impact of banks' shadow activities on bank risk presents divergent arguments, each supported by empirical evidence. One perspective suggests a positive relationship between banks' shadow activities and bank risk. For instance, Based on the US market, Gennaioli, Shleifer, & Vishny (2012) argue that shadow banking activities often lead to excessive risk-taking because new financial instruments obscure the true level of risk involved and circumvent regulations, thereby establishing a positive relationship between banks' shadow activities and bank risk. Furthermore, Plantin (2015) theoretically proposed that banks' private optimal leverage levels tend to be higher than the socially optimal levels. Therefore, even under stringent capital requirements, banks are inclined to engage in more shadow banking activities with higher leverage, thereby amplifying risk. Several empirical studies support this perspective. For example, Li & Lin (2016) found that entrusted loans, a form of shadow banking lending activity, boost bank equity returns but also increase banks' equity risk, thereby reducing bank stability. Ding, Fung, & Jia (2020) used data from Chinese banks to show that banks' shadow activities can reduce earnings volatility, credit risk, and liquidity risk. More recently, Geng, Cheng & Zhang (2021) examined Chinese banks' shadow activities through wealth management products (WMPs) and found that WMPs increase bank risk, particularly insolvency risk, portfolio risk, leverage risk, and the volatility of return on assets (ROA). Thus, the following hypothesis can be proposed:

***Hypothesis 1a.*** *Higher levels of banks' shadow activities are associated with increased bank risk in the global banking market.*

However, the other side of the argument suggests a negative relationship between banks' shadow activities and bank risk. Gennaioli, Shleifer, & Vishny (2013) argue that when banks engage in shadow activities, they tend to interconnect through markets, increasing their exposure to systematic risk while reducing idiosyncratic risk. This perspective is supported by earlier studies that explore the impact of banks' shadow activities measured by off-balance sheet (OBS) items (Avery & Berger, 1991; Hassan & Sackley, 1994), which show that OBS activities generate diversification in income streams, thereby reducing risk.

Recent studies also support this view. For instance, Milcheva, Falkenbach, & Markmann (2019) examine European banks and find that shadow activities can improve bank liquidity and funding positions, particularly through the issuance of mortgage-backed securities (MBS) in the aftermath of the financial crisis. This is further corroborated by research from Acharya, Schnabl & Suarez (2013), who demonstrate that MBS and other securitized products play a crucial role in maintaining liquidity in stressed market conditions, thus stabilizing banks' financial positions. In addition, Hasman & Samartín (2022) demonstrate that through regulatory arbitrage and off-balance sheet intermediation, banks may reduce moral hazard and risk-taking. Due to the absence of deposit insurance covering shadow banking activities, banks' investors demand higher returns to compensate for increased risk. Consequently, banks may adopt lower risk-taking strategies to maintain stability and improve investor confidence in volatile financial landscapes.

***Hypothesis 1b.*** *Higher levels of banks' shadow activities are associated with lower bank risk in the global banking market.*

## 2.2.2 The effect of bank complexity

### 2. 2.2.1 The role of banks' business complexity

Banks operate across multiple, dispersed business lines to expand their business scope and mitigate risks. While a wider scope of business enhances banks' resilience, it also brings out the issue of business complexity - defined as the width and variety of the business operations, especially in non-traditional banking activities. Banks with higher levels of business complexity engage in a wider variety of operations and strategies. As a result, this complexity can potentially moderate the relationship between banks' shadow activities and bank risk.

Business complexity may drive banks to pursue higher returns, thereby increasing their risk exposure. Marinelli et al. (2022) uncover that banks engaged in diversified and non-traditional banking activities tend to give more credit to riskier borrowers, such as those related to multiple borrowers. This finding indicates that in dealing with loan market competition, banks' diversification activities are more likely associated with their risk-taking behaviors. Also, Carbó Valverde & Rodríguez Fernández (2007) find that nontraditional banking activities significantly reduce banks' profit levels. For example, banks have opportunistically traded securities to capitalize on market opportunities. Many of these risk-seeking activities are conducted through units engaged in "proprietary trading," where a bank's own funds are used to pursue speculative returns, exposing them to significant liquidity risk. Freixas et al. (2007) further address that since complex bank groups, usually integrated and diversified financial conglomerates, are more likely to be offered bail-outs from governments, such 'safety nets' as a side-effect could encourage their risk-taking incentives and make them risk-takers.

Additionally, increased business complexity can expose banks to substantial regulatory uncertainties, thereby elevating their overall risk. Historically, regulators have tended to constrain and punish banks' diversified activities. For example, the US government imposed restrictions on business activities under the Glass-Steagall Act (GSA) of 1933 to prevent banks from becoming too diverse and complex for local authorities to understand (Christiansen & Pace, 1994). In addition to ex ante (preventive) regulations, ex post (punitive) regulations, such as the 2010 Dodd-Frank Act in the US, have also been shown to negatively impact banks that operate with de facto complexity (Freixas & Santomero, 2002; Rochet, 2004; Santos, 2000). Martynova & Vogel (2022) conduct a study on the German banking industry from 2005 to 2017. Their results supported the idea that regulatory tightness leads to an increase in related regulatory costs. Therefore, banks with business complexity may attract more supervisory attention, incurring higher compliance and monitoring costs, which in turn increases the probability of liquidity risk. Based upon this literature, hypotheses are therefore constructed as:

***Hypothesis 2:*** *The negative (positive) relationship between banks' shadow activities on bank risk is weaker (stronger) for banks with higher business complexity.*

#### 2.2.2.2 The role of banks' organizational complexity

Organizational complexity refers to the multiplicity of a bank's structural arrangement – specifically, the number and scope of legal entities established beyond its headquarter. Banks with higher levels of organizational complexity engage in a wider variety of locations and regulatory compliance issues. Consequently, this complexity potentially alters the relationship between banks' shadow activities and bank risk.

Organizational complexity exposes banks to higher risk through two primary channels: challenges in information collection and processing, and the amplification of agency problems and moral hazards. On the one hand, complex organizational structures significantly hinder the bank's ability to collect and consolidate critical information. For example, Siggelkow & Rivkin (2005) highlight how complex organizational structures may hinder the search for and acquisition of critical information, resulting in missed opportunities and heightened vulnerability to environmental turbulence. Skrastins & Vig (2019) and Liberti & Mian (2008) focus on the acquiring, transferring, and use of information flow within complex organizations and concluded that information loss among the process would lead to inferior performance. Bushman, Piotroski & Smith (2004) demonstrate that larger legal entities complicate the financial reporting process, leading to increased monitoring costs and potential information gaps. Similarly, Cetorelli & Goldberg (2016) illustrate that the intricate branch networks of conglomerate banks reduce the sensitivity of lending to funding shocks because essential data become more difficult to gather and integrate effectively. Deng & Elyasiani (2008) further highlight that greater geographic distance between a bank's headquarters and its branches elevates risk, largely due to the challenges in efficiently transferring information across geographically dispersed locations.

On the other hand, organizational complexity amplifies agency problems and moral hazards. When a bank's information flows through multiple layers of subsidiaries and branches, top management faces increased difficulties in obtaining and analyzing the data required for sound decision-making. This problem is compounded by opaque internal frameworks and fragile corporate governance (Dam & Koetter, 2012; Penas & Unal, 2004; Rajan & Zingales, 2001; Stein, 2002). Furthermore, cross-border structures introduce additional risk by increasing information costs in unfamiliar jurisdictions (Buch et al., 2013). In combination, organizational complexity heightens bank risks as it contributes to overall poorer performance, underscoring the delicate balance banks must maintain between organizational expansion and effective governance. Therefore, it is reasonable to infer that:

***Hypothesis 3:*** *The negative (positive) relationship between banks' shadow* activities *on bank risk is weaker (stronger) for banks with higher organizational complexity.*

## 2.3. Data

The primary sample contains bank groups with the necessary granular bank-level financial data from the Bureau van Dijk BankFocus database, covering the fiscal years 2008 to 2022. During this period, both researchers and policymakers first identify the problem of "banks' shadow activities" as a common concern. This timeframe includes profound changes in the global banking system that influence banks' shadow activities, making it particularly suitable for analysis.

I conduct the examination of banks' shadow activities effects at the ultimate parent level, where key strategic decisions, such as engaging in shadow banking activities, are typically made. By studying at the highest holder level, I aim to comprehensively understand the overall impact of banks' shadow activities on the entire bank group. To ensure the representativeness and availability of the dataset, I establish a minimum threshold of US$15 million on the total asset scale. This criterion ensures that the selected banks are of sufficient size and significance to accurately capture their influence on the banking sector.

### 2.3.1. Measurement of banks' shadow activities

The proxy for banks' shadow activities is the off-balance sheet item ratio (OBS), calculated as off-balance sheet items divided by total on and off-balance sheet exposures. Bank groups increasingly engage in off-balance sheet activities as part of their financial innovation efforts. These activities include a range of non-traditional banking operations that fall outside regulatory supervision, such as asset management services, securitization, derivatives trading, special purpose entities, guarantees, commitments, and other transactions. These activities represent a significant level of banks' shadow operations. A higher off-balance sheet item ratio suggests greater reliance on off-balance sheet activities, indicating a potentially larger presence of banks' shadow banking operations.

### 2.3.2. Measurement of bank complexity

To study how bank complexity affects the risks of global bank groups, I need an empirical measure of bank complexity. However, using simple quantitative indicators to define bank complexity poses challenges due to its multiple dimensions and the lack of consensus on measurement metrics. Some papers follow the framework constructed by Cetorelli & Goldberg (2014), indicating three main dimensions of complexity: business diversification, geographic diversification, and network interconnectedness. What is more, Cetorelli et al. (2014) construct two general measures—organizational complexity and business diversification—to evaluate the complexity of many global banks, revealing a continuous increase in average complexity over time.

In this study, constructing a consistent and comprehensive statistical measure of complexity on a global scale is challenging. Disclosure standards and relevant information vary among countries, and some countries may lack data. To address these challenges, I develop a consistent measurement metric suitable for all bank groups in the sample. This approach distinguishes two key dimensions of a bank group's overall complexity and differentiates between measures for each dimension.

*Banks' business complexity*

Business complexity captures the breadth of activities and business lines within a banking organization. In this study, I employ the non-interest income ratio as a proxy measure of business complexity. The non-interest income ratio is calculated by dividing non-interest income by the sum of net interest income and non-interest income. Non-interest income includes revenue generated from a variety of non-traditional lending activities, such as fees and service charges, fiduciary income, trading revenue, and other income derived from non-interest activities like advisory services, brokerage, and underwriting. Previous research, including studies by Laeven & Levine (2007) and Liang, Chen, & Chen (2016), supports the use of the non-interest income ratio as a proxy for business complexity. These studies utilize non-interest income to assess the extent of a bank's engagement in a range of activities spanning from lending-focused to non-lending-focused operations. By analyzing the non-interest income ratio, I aim to capture the proportion of a bank's total income derived from non-lending activities, providing insight into its level of business complexity. A higher non-interest income ratio indicates a greater emphasis on non-lending activities, reflecting a higher degree of business complexity within the bank.

However, it is important to note that non-interest income, as a proxy measure, only captures the share of income that is realized and reported on the income statement. It does not fully capture the level of diversity and complexity of a bank's business operations, as it does not include unrealized gains, such as revaluation surpluses of financial assets. To address this limitation and provide a more comprehensive measure of business complexity, I construct a second proxy: the ratio of net interest spread to net interest margin (NIS/NIM ratio), where:

$$
\begin{aligned}
&Net\ interest\ spread\ (NIS) \\
&\quad = Interest\ yield\ on\ earning\ assets \\
&\quad - Interest\ rates\ paid\ on\ borrowed\ funds \\
&\quad = \left(\frac{\text{Interest income}}{\text{average interest earning assets}} \right. \\
&\quad \left. - \frac{\text{Interest expense}}{\text{average interest bearing liability}}\right) \times 100\%
\end{aligned}
$$

$$Net\ interest\ margin\ (NIM) = \frac{Net\ interest\ income}{average\ interest\ earning\ assets}$$
$$= \frac{Interest\ incom - Interest\ expense}{average\ interest\ earning\ asset} = \times\ 100\%$$

From the above equations, we can see that the net interest spread [NIS] is calculated as the difference between the interest yield on earning assets and the interest rates paid on borrowed funds. It represents the difference between interest income and interest expense relative to the average interest-earning assets and interest-bearing liabilities. On the other hand, the net interest margin [NIM] is calculated as net interest income divided by the average interest-earning assets, representing the proportion of interest income to interest-earning assets. Therefore,

$$NIS - NIM = \left(\frac{Interest\ income}{average\ interest\ earning\ assets} - \frac{Interest\ expense}{average\ interest\ bearing\ liability}\right) - \frac{Interest\ incom - Interest\ expense}{average\ interest\ earning\ asset} = \frac{Interest\ expense}{average\ interest\ earning\ asset} - \frac{Interest\ expense}{average\ interest\ bearing\ liability}$$

Interest-earning assets are the assets banks create when lending funds to external parties with the expectation of earning interest. These assets include a variety of financial instruments, such as loans extended to borrowers, interbank placements, repurchase agreements, and deposits held with central banks. Interest-bearing liabilities, on the other hand, are the obligations banks incur when borrowing or attracting funds from external parties under the obligation to pay interest. These liabilities encompass financial instruments like deposits, borrowings from central banks, interbank placements, funds borrowed from other financial institutions, reverse repurchase agreements with financial institutions, margin deposits, bonds issued for capital raising purposes, and other liabilities that require interest payments. By comparing the net interest spread and net interest margin, we can gain insights into the relationship between interest-earning assets and interest-bearing liabilities. If the net interest spread exceeds the net interest margin, it suggests that the volume of interest-earning assets is smaller than that of interest-bearing liabilities. Conversely, if the net interest spread is less than the net interest margin, it indicates that the volume of interest-earning assets is larger than that of interest-bearing liabilities.

$$If\ NIS > NIM, Interest\ earning\ asset < Interest\ paid\ liability$$
$$If\ NIS < NIM, Interest\ earning\ asset > Interest\ paid\ liability$$

Simple, traditional banks that primarily focus on deposit and lending activities tend to attract a larger volume of interest-bearing liabilities. These liabilities support the creation of interest-earning assets, such as loans and other interest-generating instruments. Consequently, the total value of interest-earning assets usually exceeds that of interest-bearing liabilities, resulting in a net interest margin that is generally smaller than the net interest spread.

In contrast, banks with complex business models that engage in a wider range of activities, especially investment-related, may not generate significant interest income. As a result, the size of their interest-earning assets is often smaller than that of their interest-bearing liabilities, leading to a larger net interest spread relative to the net interest margin. To measure the business complexity of banks, I construct the NIS/NIM ratio. A higher NIS/NIM ratio indicates greater complexity in a bank's operations.

*Banks' organizational complexity*

Organizational complexity reflects the number and potential geographic dispersion of a bank's affiliated entities. A more complex structure indicates a higher level of complexity. I use three proxies to measure organizational complexity. First, following the studies of Berger & Bouwman (2013) and Berger & Roman (2015), I consider the number of bank branches to account for the degree of complexity. Second, I introduce the number of employees as a proxy. The complexity level of an organization depends significantly on the interconnections among employees and their diverse effects on the business. A larger workforce implies higher diversity and more information barriers, which can make it challenging for internal managers to control the organization and for external investors and supervisors to assess the risks (Birkinshaw & Heywood, 2010). Additionally, I use the number of acquiring events for each bank group from the Zephyr database. The Zephyr database records corporate mergers and acquisitions (M&A) of the sample bank groups from 2001 onwards, providing information on both acquiring and target companies along with descriptive details about each deal.

### 2.3.3. Measurement of bank risk

I use the natural log of non-performing loans *(ln(NPL))* and *impaired loans to equity ratio* to measure bank risk. Both metrics reflect the asset quality of bank groups: higher values indicate a greater likelihood of issues in recovering outstanding loans due to borrower defaults. Therefore, increases in *ln(NPL)* and *impaired loans to equity ratio* are directly related to higher idiosyncratic risk in banks (Bessler et al., 2015).

### 2.3.4. Control variables

In all estimations we include a vector of variables $Control_{i,t-1}$ to control for time-varying bank-specific characteristics that are other determinants of risk commonly employed in the literature (e.g. Goetz, Laeven, & Levine, 2016; Ly et al. 2018; Jiang, Levine, & Lin, 2023). I control for bank size using the natural log of total assets, for the business model with the *loan-to-assets ratio*, for earnings with the return on assets (*ROA*), for management quality with the *cost-to-income ratio*, and for financial leverage with the *equity-to-assets ratio*. To control country-level macroeconomic conditions, we use the annual *real GDP* growth rate and *core CPI* growth rate, collected from the World Bank database.

### 2.3.5. Stylish facts and summary statistics

Figures 2.1 and 2.2 present a snapshot of 2021, illustrating the basic situation of bank groups' business complexity in terms of the industrial distribution of subsidiaries in this sample set. Specifically, Figure 2.1 compares the number of financial and non-financial subsidiaries owned by the sampled bank groups. Although financial subsidiaries still dominate, non-financial subsidiaries account for a significant portion, almost 25% of the total, indicating that bank groups have largely engaged in non-financial operations.

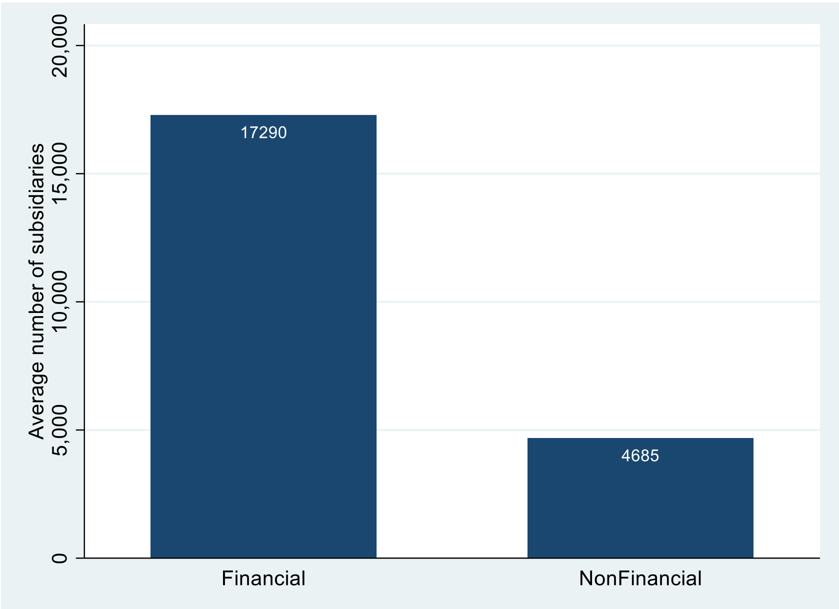



Figure 2.1: Average numbers of banks' subsidiaries

Figure 2.2 provides a perspective on the variety of non-financial industries in which bank groups participate. The industrial classification code used is NACE Rev. 2, the European statistical classification of economic activities, which classifies a business's main area of activities into 21 main sections. The complete list of classifications is shown in Appendix A1. According to Figure 2.2, Panel A, the sampled bank groups are involved in 13 main non-financial industries. The largest proportion of non-financial subsidiaries is categorized under 'L - Real Estate Activities,' followed by 'N - Administrative and Support Service Activities,' and 'M - Professional, Scientific and Technical Activities' in third place. The number of non-financial subsidiaries in these three industries is more than twice that in other industries.

Figure 2.2 also reviews the subdivisions within the financial industry. The industrial classification code applied is NACE Rev. 2 (4-digit level). The complete list of classifications is shown in Appendix A2. Within this, subsidiaries classified under 6419 (other monetary intermediation), which includes activities like receiving deposits and extending credit, unsurprisingly make up the largest proportion. Additionally, there are 22 other classes of financial subsidiaries in the sample. Notably, class 6619—Other activities auxiliary to financial services, except insurance and pension funding—includes activities such as financial transaction processing, investment advisory services, and activities of mortgage advisers and brokers. Other financial subsidiaries, such as 6420 (Activities of holding companies) and 6612 (Security and commodity contracts brokerage), also account for a significant proportion.

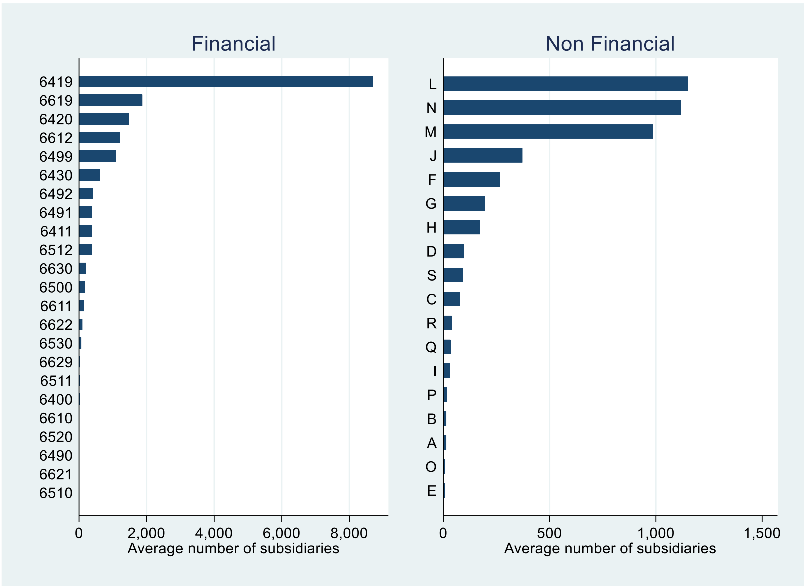



Figure 2.2: The industry distribution of banks' subsidiaries

Table 2.1 Panel A presents descriptive statistics. The data is an unbalanced panel consisting of annual financial data abstracted from at most 359 largest bank groups in the world while the number of banks may vary from year to year. In total, the dataset comprises a maximum of 4,565 bank-year observations. On average, the bank groups in the sample hold approximately 21% of off-balance sheet items in their total on and off-balance sheet exposure. There is a substantial variation across banks, with the maximum level of the examination of banks' shadow activities focuses on the ultimate group company level, where crucial business strategy decisions, such as engaging in shadow banking activities, are typically made. By studying the highest holder level, we can comprehensively understand the overall impact of banks' shadow activities on the entire bank group. To ensure the representativeness and availability of the dataset, we established a minimum threshold of US$15 million on the total asset scale. This criterion ensures that the selected banks are of sufficient size and significance to accurately capture their influence on the banking sector, particularly in terms of their off-balance sheet items ratio, which approaches approximately 80 percent. In terms of the non-interest income ratio, the average is around 35%. The variation across bank groups is larger, however, with a few clear outliers. This result is qualitatively robust considering bank groups may make either non-interest income or loss, net operating income or loss in their operation. The average NIS/NIM ratio is approximately 90%, varying from 2% to 170%. What is more, the average number of employees and the number of branches is approximately 54135 and 3687, respectively. On average, each bank group has 44 acquiring events each year. As for the two risk metrics, the average of impaired loans to equity ratio and ln(NPL) are 24% and 13%, respectively.

Table 2.1 Panel B presents the correlations among key variables. It shows a positive correlation between off-balance sheet item ratio and ln (NPL) ($r = 0.07$, $p = 0.000$), and a negative correlation between off-balance sheet item ratio and impaired loan to equity ratio, ($r$ =-0.01, $p = 0.000$). It also shows that Net loans to total asset and Cost to income ratio, have opposite associations with ln (NPL) ($r$ =- 0.087 and $r$ = – 0.047, respectively) and impaired loan to equity ratio ($r = 0.104$ and $r = 0.106$, respectively). ln(total assets) has positive correlations with both bank risk measures while ROA, Equity to asset ratio, Real GDP and CPI have negative correlations with both bank risk measures.

**Table 2.1 (Panel A):** Descriptive Statistics

| Variables | Obs | Mean | Std. Dev. | Min | Max | p1 | p99 | Skew. | Kurt. |
|---|---|---|---|---|---|---|---|---|---|
| Off Balance sheet item ratio | 4565 | 20.912 | 14.924 | 0 | 97.968 | 0.244 | 79.264 | 171.123 | 701.565 |
| Non-interest income ratio | 4565 | 32.309 | 19.510 | -2.978 | 101.335 | 2.357 | 100.463 | 122.630 | 507.245 |
| NIS/NIM | 4564 | 90.468 | 19.534 | 2.014 | 170.895 | 0.207 | 167.075 | -86.753 | 1032.139 |
| Num of employees | 4363 | 27883.976 | 54443.318 | 123 | 305072 | 328 | 305072 | 3.511 | 15.854 |
| Num of branches | 4565 | 1501.196 | 3552.821 | 1 | 23682 | 1 | 23682 | 4.575 | 26.099 |
| Num of M&A event | 4565 | 3.655 | 44.614 | 0 | 2364 | 0 | 51 | 38.977 | 1841.008 |
| Impaired loans to equity | 4448 | 23.581 | 37.735 | -0.610 | 257.570 | 0.010 | 257.57 | 4.153 | 23.219 |
| ln (NPL) | 4398 | 13.302 | 2.026 | 4.710 | 18.519 | 8.407 | 17.723 | -0.129 | 3.394 |
| ln (total assets) | 4565 | 17.805 | 1.568 | 14.845 | 21.697 | 14.873 | 21.697 | 0.653 | 2.874 |
| Net loans to total asset | 4555 | 56.705 | 15.733 | 3.990 | 85.220 | 4.050 | 85.060 | -0.957 | 4.132 |
| Cost to income | 4565 | 55.191 | 15.902 | 23.050 | 112.170 | 24.900 | 106.4 | 0.578 | 3.833 |
| Equity to assets | 4565 | 10.050 | 4.555 | 2.820 | 38.070 | 3.410 | 32.450 | 2.529 | 15.062 |
| ROA | 4565 | 1.051 | 0.965 | -2.240 | 5.690 | -2.240 | 4.710 | 0.742 | 8.706 |
| Real GDP | 4565 | 2.629 | 3.640 | -25.908 | 15.836 | -8.781 | 10.636 | -0.817 | 6.877 |
| Core CPI | 4472 | 2.903 | 4.873 | -4.863 | 154.756 | -1.931 | 15.177 | 17.227 | 477.058 |

Note: This table contains descriptive statistics of our key variables. All variables are for borrowing firms. I provide a detailed definition of each variable in Appendix A3. I winsorize all control variables at the 1st and 99th percentiles.

**Table 2.2 (Panel B):** Correlation Matrix

| VARIABLE | Off Balance sheet item ratio | Impaired loans to equity | ln(NPL) | ln(total assets) | Net loans to total assets | Cost to income | Equity to assets | ROA | Real GDP | CPI |
|---|---|---|---|---|---|---|---|---|---|---|
| Off Balance sheet item ratio | 1.000 | | | | | | | | | |
| Impaired loans to equity | -0.100*** | 1.000 | | | | | | | | |
| ln(NPL) | 0.066*** | 0.443*** | 1.000 | | | | | | | |
| ln(total assets) | 0.105*** | 0.045*** | 0.780*** | 1.000 | | | | | | |
| Net loans to total assets | 0.117*** | 0.104*** | -0.087*** | -0.220*** | 1.000 | | | | | |
| Cost to income | 0.059*** | 0.106*** | -0.047*** | -0.046*** | -0.116*** | 1.000 | | | | |
| Equity to assets | -0.007 | -0.181*** | -0.318*** | -0.351*** | -0.138*** | -0.131*** | 1.000 | | | |
| ROA | -0.002 | -0.175*** | -0.206*** | -0.107*** | -0.063*** | -0.293*** | 0.309*** | 1.000 | | |
| Real GDP | 0.032** | -0.139*** | -0.075*** | -0.005 | -0.082*** | -0.277*** | 0.025* | 0.151*** | 1.000 | |
| Core CPI | 0.012 | -0.009 | -0.022* | -0.082*** | -0.108*** | -0.137*** | 0.058*** | 0.068*** | 0.097*** | 1.000 |

Note: This table contains the correlations of key variables. All variables are for borrowing firms. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

## 2. 4. Empirical analysis

### 2.4.1 . Baseline regression:

I begin the analysis by testing *Hypothesis 1a* and *Hypothesis 1b*, that is, whether bank groups with a higher level of complexity leads to higher bank risk. To do so, I conduct the OLS regression model followed:

$$Risk_{it} = \alpha_0 + \alpha_1 BS_{i,t-1} + \sum_{1}^{k} Control_{i,t-1} + Macroecnomics_{c,t-1} + YearFE + Bank\ FE + \epsilon_{i,t}$$

[1]

Where $Risk_{it}$ is the metric of risk measures for bank $i$ in year $t$ and serve as the dependent variables. The key independent variable is $BS_{i,t-1}$, which represents the banks' shadow activities, measured by off-balance sheet item ratio (OBS). This variable examines the conditional relationship between the risk measure and the bank-specific shadow activities. The coefficient of interest in this analysis is $\alpha_1$ . The vector $Control_{i,t-1}$ includes several bank-specific determinants of risk based on prior literature, such as the *ln(total assets), net loans to total assets ratio, cost-to-income ratio, equity ratio*, and $ROA$. $Macroecnomics_{c,t-1}$ represents two control variables that measure the macroeconomic conditions of each country where banks are located. To mitigate the influence of outliers, I winsorize all continuous variables (the off-balance sheet item ratio and all control variables) at the 1% and 99% levels for each year. Furthermore, $YearFE$ denotes year fixed effects to account for global macroeconomic conditions affecting all bank groups equally, while $BankFE$ refers to bank fixed effects at the bank group level to capture unobserved firm-level characteristics. In all regression specifications, I cluster standard errors at the bank level to allow for within-bank correlation of errors over time.

The test results of the baseline regression are presented in Table 2.2 which features six columns that examine whether the off-balance sheet item ratio—a measure of banks' shadow activities—is significantly correlated with two risk metrics: *ln(NPL)* and the impaired loans to equity ratio. Columns 1 and 2 show the relationship between banks' shadow activities and *ln(NPL)* without and with controls, respectively. The results show that the off-balance sheet item ratio is negatively associated with *ln(NPL)*, and the coefficients are statistically significant. Columns 3 and 4 estimate the relationship between the banks' shadow activities measure and *impaired loans to equity ratio* without and with controls, respectively. In both cases, the coefficients are statistically significant and negative, consistent with the findings from columns 1 and 2. This suggests that higher levels of banks' shadow activities are associated with lower values of both *ln(NPL)* and *impaired loans to equity ratio*. (e.g., Haq et al., 2022; Hassan et al., 1993). It should be noted that some of the models generate high $R^2$ and this issue is further justified in the Appendix A4.

**Table 2.3**: The effect of banks' shadow activities on bank risk

| VARIABLES | (1)<br>$\ln(NPL)_{i,t}$ | (2)<br>$\ln(NPL)_{i,t}$ | (3)<br>$Impaired\ loan\ to\ equity_{i,t}$ | (4)<br>$Impaired\ loan\ to\ equity_{i,t}$ |
|---|---|---|---|---|
| $OBS_{i,t-1}$ | -0.830*** | -0.803*** | -26.786** | -23.355** |
| | (-2.59) | (-2.82) | (-2.46) | (-2.03) |
| $\ln(total\ assets)_{i,t-1}$ | | 0.986*** | | 6.048** |
| | | (12.18) | | (2.38) |
| $Net\ loans\ to\ total\ asset_{i,t-1}$ | | 0.010*** | | 0.174 |
| | | (3.00) | | (1.38) |
| $Cost\ to\ income_{i,t-1}$ | | -0.003 | | -0.044 |
| | | (-1.02) | | (-0.38) |
| $Equity\ to\ assets_{i,t-1}$ | | 0.004 | | -0.301 |
| | | (0.29) | | (-0.83) |
| $ROA_{i,t-1}$ | | -0.153*** | | -4.112*** |
| | | (-4.84) | | (-2.83) |
| $GDP_{i,t-1}$ | | -0.032*** | | -0.317 |
| | | (-6.13) | | (-1.31) |
| $CPI_{i,t-1}$ | | -0.004 | | -0.048 |
| | | (-0.93) | | (-0.43) |
| *Constant* | 13.531*** | -4.174*** | 29.539*** | -77.696 |

| | | | | |
|---|---|---|---|---|
| | (201.96) | (-2.65) | (12.98) | (-1.62) |
| *Bank FE* | YES | YES | YES | YES |
| *Year FE* | YES | YES | YES | YES |
| *Observations* | 4,130 | 4,078 | 4,171 | 4,112 |
| *R-squared* | 0.895 | 0.918 | 0.686 | 0.713 |

Note: This table presents estimates from a baseline regression model [1] examining the relationship between banks' shadow activities and bank risk. The dependent variable is bank risk, measured by *ln(NPL)* and *Impaired loans to equity*. The primary variable of interest is banks' shadow activities, measured by the off-balance sheet item ratio (*OBS*). Column 2 uses *ln(NPL)* as the dependent variable, including *Year* and *Bank* fixed effects, along with control variables such as *ln(total assets), Net loans to total asset, Cost to income, Equity to assets, ROA, Consumer Price Index (CPI),* and *GDP per Capita.* Column 1 also uses *ln(NPL)* but omits the control variables. Column 4 uses *Impaired loans to equity* as the dependent variable, including *Year* and *Bank* fixed effects, along with all control variables. Column 3 uses *Impaired loans to equity* but omits the control variables. All explanatory variables lag by one year, and standard errors are clustered at the firm level, reported in parentheses beneath coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

## 2.4.2. Robustness test

### 2.4.2.1 Alternative measures of risk

I redo the estimation of equation [1] with two alternative measures of risk (non-performance loan ratio and loan loss provision ratio) following Zhang, Cai, Dickinson, & Kutan (2016) and Lu & Nikolaev (2022). The non-performing loan ratio measures the proportion of loans that are in default or close to being in default, reflecting the quality of the bank's loan portfolio. A higher ratio indicates a higher level of risk associated with the loans. The loan loss provision ratio, on the other hand, represents the amount set aside by a bank to cover potential loan losses, expressed as a percentage of total loans. It is an indicator of how much risk the bank anticipates from its lending activities. The results are shown in Table 2.3. Reassuringly, the coefficient estimates remain negatively significant. Specifically, when using the non-performing loans ratio as the dependent variable, the coefficient is -2.663 (and -3.902 without controls). For the loan loss provision ratio as the dependent variable, the coefficient is -18.021 (and -22.428 without controls).

**Table 2.4:** Alternative measures of risk

| VARIABLES | (1)<br>$Non\ perform\ loans\ ratio_{i,t}$ | (2)<br>$Non\ perform\ loans\ ratio_{i,t}$ | (3)<br>$Loan\ loss\ prov\ ratio_{i,t}$ | (4)<br>$Loan\ loss\ prov\ ratio_{i,t}$ |
|---|---|---|---|---|
| $OBS_{i,t-1}$ | -3.902*** | -2.663* | -22.428*** | -18.021*** |
| | (-2.89) | (-1.95) | (-3.17) | (-2.74) |
| $\ln(total\ assets)_{i,t-1}$ | | 0.625* | | 8.577*** |
| | | (1.71) | | (3.66) |
| $Net\ loans\ to\ total\ asset_{i,t-1}$ | | -0.014 | | 0.246*** |
| | | (-0.79) | | (2.77) |
| $Cost\ to\ income_{i,t-1}$ | | -0.019 | | -0.267*** |
| | | (-1.24) | | (-2.99) |
| $Equity\ to\ assets_{i,t-1}$ | | 0.114* | | -0.007 |
| | | (1.68) | | (-0.02) |
| $ROA_{i,t-1}$ | | -1.025*** | | -6.150*** |
| | | (-5.58) | | (-4.58) |
| $GDP_{i,t-1}$ | | -0.094*** | | -1.022*** |
| | | (-3.17) | | (-4.71) |
| $CPI_{i,t-1}$ | | 0.088*** | | -0.255** |
| | | (3.17) | | (-2.07) |
| *Constant* | 4.475*** | -5.141 | 25.570*** | -118.223*** |
| | (15.87) | (-0.72) | (17.25) | (-2.82) |
| *Bank FE* | YES | YES | YES | YES |
| *Year FE* | YES | YES | YES | YES |
| *Observations* | 4,171 | 4,115 | 4,228 | 4,140 |
| *R-squared* | 0.683 | 0.732 | 0.477 | 0.563 |

Note: This table presents estimates from a baseline regression model [1] examining the relationship between banks' shadow activities and bank risk. The dependent variable bank risk using alternative measures. The primary variable of interest is banks' shadow activities, measured by the *off-balance sheet item ratio (OBS)*. Column 2 uses *non-perform loans ratio* as the dependent variable, including Year and Bank fixed effects, along with control variables such as *ln(total assets), Net loans to total asset, Cost to income, Equity to assets, ROA, Consumer Price Index (CPI),* and *GDP per Capita*. Column 1 also uses *non-perform loans ratio* but omits the control variables. Column 4 uses *Loan loss provision ratio* as the dependent variable, including Year and Bank fixed effects, along with all control variables. Column 3 uses *Loan loss provision ratio* but omits the control variables. All explanatory variables lag by one year, and standard errors are clustered at the firm level, reported in parentheses beneath coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

### 2.4.2.2 Additional control variable of opacity

The negative relationship between banks' shadow activities and bank risk might stem from the fact that the off-balance sheet item ratio, a proxy for shadow activities, represents not only the level of these activities but also the opacity of financial reports. Banks often incorporate a wide range of off-balance sheet items to conceal information, reducing regulators' and shareholders' ability to assess their health. This practice, which hides information about the quality of asset holdings, is relatively common and complicates the processing of existing information about banks' assets (Fosu, Ntim, Coffie, & Murinde, 2017). Consequently, the off-balance sheet item ratio acts as a confounding factor, raising concerns about endogeneity in the analysis.

To address potential estimation bias from this confounding problem, I introduce an additional control variable, $Opacity_{i,t-1}$, measured by the ratio of other operating expense to total operating expense. This measure captures the level of financial report transparency and its influence on the relationship between shadow activities and bank risk. Including this opacity proxy as a control variable is based on the rationale that banks with more transparent financial reports disclose more detailed information, while higher levels of 'other' operating expenses suggest greater ambiguity and lack of clarity. By incorporating this control variable, the analysis accounts for the confounding effect of opacity, helping to minimize potential bias and improve the robustness of the findings.

The results in Table 2.4 support the baseline regression, indicating that banks engaging in more shadow banking activities tend to have lower risks. The off-balance sheet item ratio remains significantly negatively related to all bank risk measures. Specifically, the coefficient for *off-balance sheet item ratio* regressed on *ln(NPL)* decreases slightly from -0.803 to -0.838. The coefficient for *off-balance sheet item ratio* regressed on the *impaired loans to equity ratio* shows a minimal change, decreasing from -23.355 to -23.881.

**Table 2.5:** Additional control variable of opacity

| VARIABLES | (1) $\ln(NPL)_{i,t}$ | (2) $Impaired\ loan\ to\ equity_{i,t}$ |
|---|---|---|
| $OBS_{i,t-1}$ | -0.838*** | -23.881** |
| | (-2.89) | (-2.06) |
| $Opacity_{i,t-1}$ | 0.220*** | 2.738 |
| | (4.61) | (1.02) |
| $ln\ (total\ assets)_{i,t-1}$ | 0.778*** | 3.502 |
| | (8.61) | (1.13) |
| $Net\ loans\ to\ total\ asset_{i,t-1}$ | 0.010*** | 0.174 |
| | (3.00) | (1.40) |
| $Cost\ to\ income_{i,t-1}$ | -0.002 | -0.032 |
| | (-0.60) | (-0.28) |
| $Equity\ to\ assets_{i,t-1}$ | -0.001 | -0.372 |
| | (-0.04) | (-1.04) |
| $ROA_{i,t-1}$ | -0.172*** | -4.355*** |
| | (-5.31) | (-2.97) |
| $GDP_{i,t-1}$ | -0.032*** | -0.316 |
| | (-6.11) | (-1.30) |
| $CPI_{i,t-1}$ | -0.002 | -0.021 |
| | (-0.42) | (-0.19) |
| *Constant* | -3.456** | -69.240 |
| | (-2.19) | (-1.48) |
| *Bank FE* | YES | YES |
| *Year FE* | YES | YES |
| *Observations* | 4,068 | 4,102 |
| *R-squared* | 0.920 | 0.713 |

Note: This table presents estimates from a baseline regression model [1] examining the relationship between banks' shadow activities and bank risk with additional control variable of opacity. The primary variable of interest is banks' shadow activities, measured by the *off-balance sheet item ratio (OBS)*. Column 1 uses *ln (NPL)* as the dependent variable and Column 2 uses *Impaired loans to equity* as the dependent variable. Both Columns include *Year* and *Bank* fixed effects, along with control variables such as *ln(total assets), Net loans to total asset, Cost to income, Equity to assets, ROA, Consumer Price Index (CPI),* and *GDP per Capita*. All explanatory variables lag by one year, and standard errors are clustered at the firm level, reported in parentheses beneath coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

#### 2.4.2.3 PSM-DID

In addition to the endogenous variable concern due to confounding factors, another identification concern is the possibility of reverse causation from bank group risk to banks' shadow activities. For instance, it is plausible that bank risk influences the level of banks' shadow activities through channels related to asset impairment. Furthermore, increasing bank risk may prompt bank groups to adopt a more aggressive approach in expanding and developing their shadow banking strategies. However, I address these endogeneity concerns through the following strategies. First, all explanatory variables, including measures of banks' shadow activities and control variables, lag by one period in the regression analysis. This ensures that the measurement of these variables precedes the occurrence of operational losses at the banks. By incorporating these lags, the potential influence of reverse causality is alleviated.

Second, I conduct a Propensity Score Matching-Difference-in-Differences (PSM-DID) analysis as an alternative identification strategy, using the designation of Global Systemically Important Banks (GSIBs) as the treatment in the DID analysis, following the methodology outlined by Ho, Wong, and Tan (2022). The concept of GSIBs emerged in response to the 2008 global financial crisis, which highlighted the systemic risks posed by large, complex financial institutions whose failure could have widespread negative impacts on the global economy. Since 2011, the Financial Stability Board (FSB), in collaboration with the Basel Committee on Banking Supervision (BCBS) and national authorities, has been responsible for identifying and regulating GSIBs. These banks are identified based on five categories of systemic importance: size, interconnectedness, complexity, substitutability, and cross-jurisdictional activities. For each category, the framework uses specific indicators to quantify the bank's systemic importance, and the BCBS calculates a systemic importance proxy, known as the GSIB score, which is the weighted average of these 12 indicators. Banks are designated G-SIBs if their GSIB scores exceed a predetermined threshold. Based on their scores, banks are assigned to one of five categories, or "buckets" (BIS, 2018).

The designation of a bank as a GSIB significantly decreases banks' shadow activities. Firstly, GSIBs are subject to more intensive supervisory scrutiny regarding risk management and governance to ensure they can absorb losses and continue operating during financial stress. This includes additional capital requirements and liquidity standards that reduce the capital and liquidity available for banks to engage in banks' shadow transactions. Secondly, GSIBs are subject to an additional capital surcharge based on their systemic importance score, which ranges from 1% to 3.5% of risk-weighted assets (RWA). This surcharge is costly and encourages GSIBs to contract their off-balance sheet and become less systemic important. To test this inference, I run a DID analysis to examine the effect of GSIB designation on banks' shadow activities measure, that is, the off-balance sheet ratio.

As the designation of GSIBs is determined based on the BCBS calculation, which is a non-random assignment, this may pose concerns about the validity of the parallel trend assumption underlying the DID estimation. To address this, I perform a Propensity Score Matching (PSM) method to balance the pre-treatment characteristics of GSIBs and non-GSIBs. The matching variables are the same as those used in baseline regression. I use the radius matching method and a caliper of 0.01 to ensure common support. Figure 2.3 shows the percent bias for each covariate before and after the matching process. Most of the standardized bias are less than 10% which indicates an effective matching process.

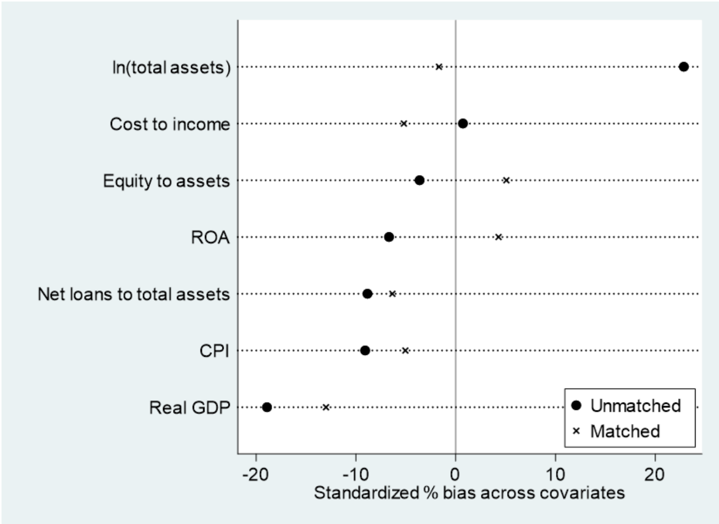



Figure 2.3: Standardized % bias across covariates

Note: This figure shows the standardized percentage bias across covariates after matching.

In Table 2.5, the result shows that GSIBs are, on average, engaging in less off-balance sheet activities than non-GSIBs. In line with expectations, after the designation of GSIBs, banks are found to have reduced their banks' shadow activities.

**Table 2.6**: The PSM-DIDs analysis of banks' shadow activities

| VARIABLES | (1)<br>$OBS_{i,t}$ |
|---|---|
| $GSIB_i$*$Post_t$ | -0.075*** |
| | (-3.32) |
| $\ln(total\ assets)_{i,t}$ | 0.001 |
| | (0.80) |
| $Net\ loans\ to\ total\ asset_{i,t}$ | 0.015 |
| | (1.65) |
| $Cost\ to\ income_{i,t}$ | -0.001* |
| | (-1.98) |
| $Equity\ to\ assets_{i,t}$ | -0.052*** |
| | (-2.76) |
| $ROA_{i,t}$ | 0.004 |
| | (1.36) |
| $GDP_{i,t}$ | -0.003 |
| | (-0.62) |
| $CPI_{i,t}$ | -0.003 |
| | (0.01) |

| | |
|---|---|
| *Constant* | 1.104* |
| | (1.87) |
| *Bank FE* | YES |
| *Year FE* | YES |
| *Observations* | 136 |
| *R-squared* | 0.973 |

Note: This table reports the results for a DIDs analysis which assess the effect of the GSIB regulatory framework on the banks' shadow activities. The dependent variable is banks' shadow activities, measured by *off-balance sheet item ratio*. *Post* is a time dummy variable which equals to one after year 2011 when the BSCB GSIB assessment methodology was introduced and zero otherwise. *GSIB* is a treatment variable which takes on one if the bank has been designated as GSIB at least once over the sample period. Standard errors are clustered at the firm level, reported in parentheses below coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Then I use this empirical setting to evaluate how the GSIB regulation influences bank risk measures. The results in Table 2.6 show that the designation of GSIBs has a significant positive impact on both *ln(NPL)* and *impaired loans to equity ratio*. This suggests that the banks' risk levels increased following the regulatory changes. After the designation of GSIBs, banks decrease their off-balance sheet activities, which leads to an increase in bank risk. This shift suggests that banks may have reallocated their risk to on-balance sheet activities under the new regulatory constraints. This finding is consistent with the baseline model, which suggests a negative relationship between off-balance sheet activities and bank risk.

**Table 2.7**: The DIDs analysis of bank risk

| VARIABLES | (1) $\ln(NPL)_{i,t}$ | (2) $Impaired\ loan\ to\ equity_{i,t}$ |
|---|---|---|
| $GSIB_i$*$post_{i,t}$ | 0.704** | 47.428*** |
| | (2.58) | (4.65) |
| $OBS_{i,t}$ | 1.247*** | 9.245* |
| | (6.77) | (1.91) |
| $\ln(total\ assets)_{i,t}$ | 0.015 | 0.250 |
| | (0.91) | (0.82) |
| $Net\ loans\ to\ total\ asset_{i,t}$ | 0.137 | -4.509** |
| | (1.45) | (-2.65) |
| $Cost\ to\ income_{i,t}$ | -0.012** | -0.394** |
| | (-2.07) | (-2.26) |
| $Equity\ to\ assets_{i,t}$ | -0.395** | -15.319*** |
| | (-2.28) | (-3.47) |
| $ROA_{i,t}$ | -0.046** | -0.976** |
| | (-2.70) | (-2.38) |
| $GDP_{i,t}$ | -0.043 | -0.348 |
| | (-1.34) | (-0.59) |
| $CPI_{i,t}$ | -0.042 | -0.348 |
| | (0.03) | (0.59) |
| *Constant* | -10.669** | -140.803 |
| | (-2.49) | (-1.26) |
| *Bank FE* | YES | YES |
| *Year FE* | YES | YES |
| *Observations* | 159 | 159 |
| *R-squared* | 0.932 | 0.937 |

Note: This table reports the results for a DIDs analysis which assesses the effect of the GSIB regulatory framework on the banks' risk measures. The dependent variables are bank risk, measured by *ln(NPL)* and *Impaired loans to equity* in Column 1 and 2 respectively. *Post* is a time dummy variable which equals to one after the year 2011 when the BSCB GSIB assessment methodology was introduced and zero otherwise. *GSIB* is a treatment variable which takes on one if the bank has been designated as GSIB at least once over the sample period. Standard errors are clustered at the firm level, reported in parentheses beneath coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

## 2.4.3. The effect of bank complexity

In this subsection, I test hypotheses 2 and 3 by augmenting the baseline regression with interactions between the banks' shadow activities measures and bank complexity measures. Specifically, I estimate the following equation:

$$Risk_{it} = \beta_0 + \beta_1 BS_{i,t-1} + \beta_2 Complexity_{i,t-1} + \beta_3 Complexity_{i,t-1} * BS_{i,t-1} + \sum_{1}^{k} Control_{i,t-1} + Macroecnomics_{c,t-1} + YearFE + BankFE + \epsilon_{i,t}$$

[2]

where $Risk_{it}$ represents the risk measures. $BS_{i,t-1}$ is the banks' shadow activities measure. $Control_{k,t-1}$ is a set of bank-level control variables described in Section 3. $Macroecnomics_{c,t-1}$ represents control variables that measure the macroeconomic conditions and $\epsilon_{i,t}$ is the residual term. $\beta_3$ is the interest of coefficient, estimates of the interactions between the complexity measures and banks' shadow activities measures. The proxy of complexity measures applied here is *non-interest income ratio*, *NIS/NIM ratio*, *number of employees, number of branches* and *number of M&A events*. What is more, $YearFE$ denotes year fixed effects accounting for global macroeconomic conditions affecting all bank groups to the same degree. $BankFE$ denotes that a bank fixed effects at the bank group level capturing unobserved firm-level characteristics. In all regression specifications, I cluster standard errors at the bank level to allow errors correlated within banks among years.

Table 2.7 shows the estimated results of equation 4. In Table 2.7 (Panel A), where ln(NPL) is used as the dependent variable, most of the coefficients of interaction terms are statistically significant and positive. The coefficients for the interaction between business complexity proxies (non-interest income ratio and NIS/NIM ratio) and the banks' shadow activities proxy (off-balance sheet item ratio) are significantly positive.

This indicates that the negative relationship between banks' shadow activities and bank risk is weakened for banks with high business complexity compared to those with low complexity. For the organizational complexity proxies, the interaction terms with banks' shadow activities—such as the number of employees and number of branches—are mostly significantly positive. These results align with the conjecture that bank complexity may offset the risk reduction typically associated with banks' shadow activities.

To validate the robustness of these findings, I extend the analysis by replacing the dependent variable with another risk indicator, *impaired loans to equity ratio*. The results, shown in Table 2.7 (Panel B), consistently indicate positive coefficients on the interaction terms, further supporting the observed patterns.

**Table 2.8 (Panel A)**: The effect of bank complexity: ln(NPL)

| VARIABLES | (1) $\ln(NPL)_{i,t}$ | (2) $\ln(NPL)_{i,t}$ | (3) $\ln(NPL)_{i,t}$ | (4) $\ln(NPL)_{i,t}$ | (5) $\ln(NPL)_{i,t}$ |
|---|---|---|---|---|---|
| $OBS_{i,t-1}* Non-interest\ income\ ratio_{i,t-1}$ | 0.017* | | | | |
| | (1.93) | | | | |
| $OBS_{i,t-1}*NIS/NIM_{i,t-1}$ | | 0.022** | | | |
| | | (2.49) | | | |
| $OBS_{i,t-1}* Num\ of\ employees_{i,t-1}$ | | | 0.000*** | | |
| | | | (4.37) | | |
| $OBS_{i,t-1}*Num\ of\ Branches_{i,t-1}$ | | | | 0.353*** | |
| | | | | (5.68) | |
| $OBS_{i,t-1}* M\&A\ events_{i,t-1}$ | | | | | 2.080 |
| | | | | | (0.65) |
| $OBS_{i,t-1}$ | -1.424*** | | -1.453*** | -1.261*** | -0.841*** |
| | (-2.99) | | (-4.04) | (-4.12) | (-2.84) |
| $Non-interest\ income\ ratio_{i,t-1}$ | -0.001 | | | | |
| | (-0.23) | | | | |
| $NIS/NIM_{i,t-1}$ | | -0.000 | | | |
| | | (-0.05) | | | |
| $Num\ of\ employees_{i,t-1}$ | | | 0.000** | | |
| | | | (2.26) | | |
| $Num\ of\ Branches_{i,t-1}$ | | | | -0.005 | |
| | | | | (-0.24) | |
| $M\&\ events_{i,t-1}$ | | | | | -0.206 |
| | | | | | (-0.36) |
| $ln\ (total\ assets)_{i,t-1}$ | 0.983*** | 0.987*** | 0.898*** | 0.964*** | 0.979*** |

| | | | | | |
|---|---|---|---|---|---|
| | (11.99) | (11.70) | (10.35) | (11.82) | (11.90) |
| $Net\ loans\ to\ total\ asset_{i,t-1}$ | 0.009*** | 0.010*** | 0.009** | 0.009*** | 0.009*** |
| | (2.79) | (2.97) | (2.56) | (2.67) | (2.64) |
| $Cost\ to\ income_{i,t-1}$ | -0.003 | -0.002 | -0.005 | -0.003 | -0.003 |
| | (-1.11) | (-0.72) | (-1.60) | (-1.15) | (-1.10) |
| $Equity\ to\ assets_{i,t-1}$ | 0.004 | 0.009 | 0.002 | 0.004 | 0.004 |
| | (0.29) | (0.64) | (0.10) | (0.27) | (0.27) |
| $ROA_{i,t-1}$ | -0.164*** | -0.153*** | -0.164*** | -0.159*** | -0.164*** |
| | (-5.11) | (-4.82) | (-5.01) | (-5.12) | (-5.11) |
| $GDP_{i,t-1}$ | -0.033*** | -0.040*** | -0.029*** | -0.030*** | -0.032*** |
| | (-6.20) | (-5.55) | (-5.30) | (-5.61) | (-6.12) |
| $CPI_{i,t-1}$ | -0.004 | -0.016** | -0.004 | -0.003 | -0.004 |
| | (-0.89) | (-2.17) | (-0.88) | (-0.83) | (-0.92) |
| *Constant* | -4.061** | -4.282*** | -2.647 | -3.766** | -3.997** |
| | (-2.51) | (-2.64) | (-1.59) | (-2.38) | (-2.49) |
| *Bank FE* | YES | YES | YES | YES | YES |
| *Year FE* | YES | YES | YES | YES | YES |
| *Observations* | 4,081 | 4,077 | 3,887 | 4,081 | 4,081 |
| *R-squared* | 0.918 | 0.919 | 0.924 | 0.920 | 0.918 |

Note: This panel reports the results for equation [2], which aims to assess the interaction term between the banks' shadow activities measure and various complexity measures. The dependent variable is *ln(NPL)*.

**Table 2.7 (Panel B):** The effect of bank complexity: Impaired loans to equity

| VARIABLES | (1) $Impaired\ loan\ to\ equity_{i,t}$ | (2) $Impaired\ loan\ to\ equity_{i,t}$ | (3) $Impaired\ loan\ to\ equity_{i,t}$ | (4) $Impaired\ loan\ to\ equity_{i,t}$ | (5) $Impaired\ loan\ to\ equity_{i,t}$ |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| $OBS_{i,t-1}$* $Non-interest\ income\ ratio_{i,t-1}$ | 0.545* | | | | |
| | (1.73) | | | | |
| $OBS_{i,t-1}$*$NIS/NIM_{i,t-1}$ | | 0.861*** | | | |
| | | (4.82) | | | |
| $OBS_{i,t-1}$* $Num\ of\ employees_{i,t-1}$ | | | 0.000* | | |
| | | | (1.80) | | |
| $OBS_{i,t-1}$*$Num\ of\ Branches_{i,t-1}$ | | | | 7.456** | |
| | | | | (2.38) | |
| $OBS_{i,t-1}$* $M\&A\ events_{i,t-1}$ | | | | | 158.484* |
| | | | | | (1.77) |
| $OBS_{i,t-1}$ | -43.329** | | -35.041** | -32.085*** | -24.399** |
| | (-2.17) | | (-2.48) | (-2.75) | (-2.06) |
| $Non-interest\ income\ ratio_{i,t-1}$ | -0.061 | | | | |
| | (-0.52) | | | | |
| $NIS/NIM_{i,t-1}$ | | -0.240*** | | | |
| | | (-2.95) | | | |
| $Num\ of\ employees_{i,t-1}$ | | | 0.000 | | |
| | | | (1.62) | | |
| $Num\ of\ Branches_{i,t-1}$ | | | | 1.022 | |
| | | | | (1.06) | |
| $M\&A\ events_{i,-1}$ | | | | | -25.588 |
| | | | | | (-1.55) |
| $\ln(total\ assets)_{i,t-1}$ | 6.110** | 6.329** | 4.450 | 5.465** | 6.042** |
| | (2.42) | (2.47) | (1.63) | (2.15) | (2.38) |
| $Net\ loans\ to\ total\ asset_{i,t-1}$ | 0.160 | 0.170 | 0.161 | 0.169 | 0.176 |
| | (1.25) | (1.36) | (1.27) | (1.35) | (1.39) |
| $Cost\ to\ income_{i,t-1}$ | -0.054 | -0.038 | -0.078 | -0.049 | -0.045 |
| | (-0.48) | (-0.32) | (-0.64) | (-0.43) | (-0.39) |
| $Equity\ to\ assets_{i,t-1}$ | -0.287 | -0.269 | -0.314 | -0.307 | -0.299 |
| | (-0.77) | (-0.74) | (-0.85) | (-0.86) | (-0.83) |

| | | | | | |
|---|---|---|---|---|---|
| $ROA_{i,t-1}$ | -4.242*** | -4.193*** | -4.059*** | -3.995*** | -4.117*** |
| | (-2.85) | (-2.85) | (-2.72) | (-2.78) | (-2.83) |
| $GDP_{i,t-1}$ | -0.326 | -0.485* | -0.357 | -0.475* | -0.491* |
| | (-1.35) | (-1.76) | (-1.19) | (-1.73) | (-1.79) |
| $CPI_{i,t-1}$ | -0.050 | -0.151 | -0.153 | -0.115 | -0.152 |
| | (-0.45) | (-0.93) | (-0.92) | (-0.79) | (-0.94) |
| *Constant* | -75.799 | -82.411* | -50.775 | -69.541 | -77.467 |
| | (-1.56) | (-1.71) | (-0.99) | (-1.45) | (-1.61) |
| *Bank FE* | YES | YES | YES | YES | YES |
| *Year FE* | YES | YES | YES | YES | YES |
| *Observations* | 4,115 | 4,111 | 3,918 | 4,112 | 4,112 |
| *R-squared* | 0.713 | 0.713 | 0.719 | 0.716 | 0.713 |

Note: This panel reports the results for equation [2], which aims to assess the interaction term between the banks' shadow activities measure and various complexity measures. The dependent variable is *Impaired loans to equity*. Standard errors are clustered at the firm level, reported in parentheses below coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

### 2.4.4. Additional analysis

#### 2.4.4.1 Internal capital market

The existing literature highlights the value of internal capital markets within banks, as they enhance performance by improving liquidity management. Billett & Mauer (2003) suggest that, due to frictions in external capital markets, internally generated funds in diversified firms can efficiently pool and allocate resources to the best opportunities, benefiting the firms. From a group perspective, a well-established internal capital market can moderate risk for banks with higher business complexity (Cetorelli et al., 2014 ,2012). Banks with business complexity often have multiple income streams across diverse business activities (Laeven & Levine, 2009). This orchestration enhances internal financing operations and improves the ability of both affiliates and the parent company to share risks by reallocating resources. During recessions, firms tend to diversify their investment needs and cash flows across industries (Matvos et al., 2018).

In addition, a robust internal capital market benefits banks with higher organizational complexity. Matvos et al. (2018) show that large, diversified publicly traded firms can expand their business when external capital market frictions are high, leading to increased mergers and acquisitions among stand-alone and diversified firms. Similar patterns are observed in banks. Houston, James, & Marcus (1997) find that bank holding companies can establish internal capital markets to efficiently allocate scarce capital among subsidiaries. Mukherjee & Pana (2018) demonstrate that internal capital markets strengthen subsidiaries, supported by regulatory requirements that mandate bank holding companies to act as a source of strength. Avramidis, Asimakopoulos, Malliaropulos & Travlos (2021) show that internal capital markets reduce the default probability of subsidiaries.

Establishing an effective internal financial market requires higher levels of bank capital. Banks hold capital for two main reasons: regulatory requirements and voluntary reserves. For instance, Basel III imposes minimum capital requirements, including a 4.5% common equity requirement and an additional 2.5% buffer, totaling a 7% minimum. Banks may also voluntarily exceed these requirements to ensure internal capital market flow, using reserves as buffers during financial stress, thus reducing liquidity and credit crises.

Therefore, I use the capital adequacy ratio as a proxy for the internal capital market and test whether a higher capital adequacy ratio (captured by the CET1 ratio) can reduce the marginal effect of bank complexity on banks' shadow activities and risk.

To do this test, I augment the baseline setup by interacting with the banks' shadow activities measures with banks' complexity measures and capital adequacy ratio. Specifically, I estimate the following equation:

$$\begin{aligned} Risk_{it} = \gamma_0 &+ \gamma_1 BS_{i,t-1} + \gamma_2 Complexity_{i,t-1} + \gamma_3 CET1_{i,t-1} + \gamma_4 Complexity_{i,t-1} \\ &* CET1_{i,t-1} + \gamma_5 Complexity_{i,t-1} * BS_{i,t-1} + \gamma_6 CET1_{i,t-1} * BS_{i,t-1} + \gamma_7 BS_{i,t-1} \\ &* Complexity_{i,t-1} * CET1_{i,t-1} \\ &+ \sum_1^k Control_{i,t-1} + Macroecnomics_{c,t-1} + YearFE + BankFE + \epsilon_{i,t} \end{aligned}$$

[3]

where $Risk_{it}$ is the matrices of risk measures. $BS_{i,t-1}$ is the banks' shadow activities measure. $Control_{k,t-1}$ is a set of bank-level control variables described in Section 3. $Macroecnomics_{c,t-1}$ represents control variables that measure the macroeconomic conditions and $\epsilon_{i,t}$ is the residual term. $\gamma_7$ is the interest of coefficient, estimates of the interactions between capital adequacy ratio, the complexity measures and banks' shadow activities measure. The proxy of capital adequacy ratio applied here is the Common Equity Tier 1 (CET1) ratio, which is calculated by taking a bank's core capital relative to its risk-weighted assets. The core capital in banks refers to Tier 1 common equity, covering liquid bank holdings such as cash, stock, etc. What is more,

$YearFE$ denotes year fixed effects accounting for global macroeconomic conditions affecting all bank groups to the same degree. $BankFE$ denotes that a bank fixed effects at the bank group level capturing unobserved firm-level characteristics. In all regression specifications, I cluster all standard errors at the bank level to allow errors correlated within banks among years.

**Table 2. 9 (Panel A)** The effect of internal capital market: Impaired loans to equity

| VARIABLES | (1)<br>$Impaired\ loan\ to\ equity_{i,t}$ | (2)<br>$Impaired\ loan\ to\ equity_{i,t}$ | (3)<br>$Impaired\ loan\ to\ equity_{i,t}$ | (4)<br>$Impaired\ loan\ to\ equity_{i,t}$ | (5)<br>$Impaired\ loan\ to\ equity_{i,t}$ |
|---|---|---|---|---|---|
| $OBS_{i,t-1}$*$CET1ratio_{i,t-1}$*$Non-interest\ income\ ratio_{i,t-1}$ | -0.042 | | | | |
| | (-0.79) | | | | |
| $OBS_{i,t-1}$*$CET1ratio_{i,t-1}$*$NIS/NIM_{i,t-1}$ | | -1.180 | | | |
| | | (0.25) | | | |
| $OBS_{i,t-1}$*$CET1ratio_{i,t-1}$*$Num\ of\ employees_{i,t-1}$ | | | -0.000* | | |
| | | | (-1.92) | | |
| $OBS_{i,t-1}$*$CET1ratio_{i,t-1}$*$Num\ of\ Branches_{i,t-1}$ | | | | -0.363 | |
| | | | | (-1.29) | |
| $OBS_{i,t-1}$*$CET1ratio_{i,t-1}$*$M\&A\ events_{i,t-1}$ | | | | | -42.462 |
| | | | | | (-1.39) |
| $OBS_{i,t-1}$*$CET1ratio_{i,t-1}$ | 1.822 | 0.602 | 0.902 | 0.756 | 0.769 |
| | (0.70) | (0.47) | (0.67) | (0.53) | (0.63) |

| | | | | | |
|---|---|---|---|---|---|
| $OBS_{i,t-1}$* $Non-interest\ income\ ratio_{i,t-1}$ | 1.278 | | | | |
| | (1.55) | | | | |
| $OBS_{i,t-1}$*$NIS/NIM_{i,t-1}$ | | -65.962 | | | |
| | | (-0.94) | | | |
| $OBS_{i,t-1}$* $Num\ of\ employees_{i,t-1}$ | | | 0.001** | | |
| | | | (2.51) | | |
| $OBS_{i,t-1}$*$Num\ of\ Branches_{i,t-1}$ | | | | 14.802** | |
| | | | | (2.56) | |
| $OBS_{i,t-1}$* $M\&A\ events_{i,t-1}$ | | | | | 644.487** |
| | | | | | (1.98) |
| $CET1ratio_{i,t-1}$*$Non-interest\ income\ ratio_{i,t-1}$ | -0.007 | | | | |
| | (-0.82) | | | | |
| $CET1ratio_{i,t-1}$*$NIS/NIM_{i,t-1}$ | | -0.459 | | | |
| | | (-0.35) | | | |
| $CET1ratio_{i,t-1}$*$Num\ of\ employees_{i,t-1}$ | | | 0.000* | | |
| | | | (1.70) | | |
| $CET1ratio_{i,t-1}$*$Num\ of\ Branches_{i,t-1}$ | | | | 0.118 | |
| | | | | (0.84) | |
| $CET1ratio_{i,t-1}$*$M\&A\ events_{i,t-1}$ | | | | | 14.227 |
| | | | | | (1.10) |

| | | | | | |
|---|---|---|---|---|---|
| $OBS_{i,t-1}$ | -82.201* | -44.927* | -60.482** | -57.275** | -43.823** |
| | (-1.94) | (-1.93) | (-2.51) | (-2.45) | (-1.99) |
| $CET1ratio_{i,t-1}$ | 0.283 | -0.019 | -0.160 | -0.110 | -0.047 |
| | (0.37) | (-0.03) | (-0.29) | (-0.20) | (-0.09) |
| $Non-interest\ income\ ratio_{i,t-1}$ | -0.065 | | | | |
| | (-0.49) | | | | |
| $NIS/NIM_{i,t-1}$ | | -3.584 | | | |
| | | (-0.69) | | | |
| $Num\ of\ employees_{i,t-1}$ | | | 0.000 | | |
| | | | (0.63) | | |
| $Num\ of\ Branches_{i,t-1}$ | | | | -1.024 | |
| | | | | (2.06) | |
| $M\&A\ events_{i,t-1}$ | | | | | -182.789 |
| | | | | | (-1.35) |
| $\ln(total\ assets)_{i,t-1}$ | 6.343** | 6.030** | 4.631 | 5.803** | 6.419** |
| | (2.23) | (2.23) | (1.51) | (1.97) | (2.24) |
| $Net\ loans\ to\ total\ asset_{i,t-1}$ | 0.143 | 0.184 | 0.149 | 0.164 | 0.171 |
| | (0.99) | (1.33) | (1.12) | (1.26) | (1.29) |
| $Cost\ to\ income_{i,t-1}$ | -0.062 | -0.071 | -0.106 | -0.076 | -0.069 |
| | (-0.47) | (-0.53) | (-0.76) | (-0.58) | (-0.51) |
| $Equity\ to\ assets_{i,t-1}$ | -0.224 | -0.332 | -0.322 | -0.299 | -0.325 |
| | (-0.63) | (-0.93) | (-0.92) | (-0.90) | (-0.96) |
| $ROA_{i,t-1}$ | -4.834*** | -4.726*** | -4.659** | -4.589*** | -4.756*** |
| | (-2.79) | (-2.71) | (-2.55) | (-2.64) | (-2.69) |

| | | | | | |
|---|---|---|---|---|---|
| $GDP_{i,t-1}$ | -0.337 | -0.336 | -0.177 | -0.221 | -0.330 |
| | (-1.22) | (-1.24) | (-0.58) | (-0.78) | (-1.19) |
| $CPI_{i,t-1}$ | -0.062 | -0.076 | -0.047 | -0.029 | -0.056 |
| | (-0.53) | (-0.58) | (-0.40) | (-0.28) | (-0.47) |
| *Constant* | -76.741 | -72.723 | -47.461 | -69.581 | -79.394 |
| | (-1.38) | (-1.38) | (-0.80) | (-1.23) | (-1.42) |
| *Bank FE* | YES | YES | YES | YES | YES |
| *Year FE* | YES | YES | YES | YES | YES |
| *Observations* | 3,660 | 3,658 | 3,492 | 3,660 | 3,660 |
| *R-squared* | 0.715 | 0.714 | 0.721 | 0.718 | 0.714 |

Note: This table reports the results for equation [3], which aims to assess the three-way interaction terms between the banks' shadow activities measure, various complexity measures and *CET1 ratio*. The dependent variable is Impaired loans to equity.

**Table 2.8 (Panel B)** The effect of internal capital market: ln(NPL)

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| VARIABLES | $\ln(NPL)_{i,t}$ | $\ln(NPL)_{i,t}$ | $\ln(NPL)_{i,t}$ | $\ln(NPL)_{i,t}$ | $\ln(NPL)_{i,t}$ |
| $OBS_{i,t-1}$*$CET1ratio_{i,t-1}$*$Non-interest\ income\ ratio_{i,t-1}$ | -0.003 | | | | |
| | (-1.46) | | | | |
| $OBS_{i,t-1}$*$CET1ratio_{i,t-1}$*$NIS/NIM_{i,t-1}$ | | -0.022 | | | |
| | | (0.10) | | | |
| $OBS_{i,t-1}$*$CET1ratio_{i,t-1}$*$Num\ of\ employees_{i,t-1}$ | | | -0.000*** | | |

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | | | (-3.39) | | |
| $OBS_{i,t-1}$*$CET1ratio_{i,t-1}$*$Num\ of\ Branches_{i,t-1}$ | | | | -0.014** | |
| | | | | (-2.02) | |
| $OBS_{i,t-1}$*$CET1ratio_{i,t-1}$*$M\&A\ events_{i,t-1}$ | | | | | -2.334* |
| | | | | | (-1.72) |
| $OBS_{i,t-1}$*$CET1ratio_{i,t-1}$ | 0.155* | 0.054 | 0.077 | 0.065 | 0.065 |
| | (1.84) | (1.19) | (1.53) | (1.37) | (1.43) |
| $OBS_{i,t-1}$* $Non-interest\ income\ ratio_{i,t-1}$ | 0.059** | | | | |
| | (2.34) | | | | |
| $OBS_{i,t-1}$*$NIS/NIM_{i,t-1}$ | | -1.864 | | | |
| | | (-0.64) | | | |
| $OBS_{i,t-1}$* $Num\ of\ employees_{i,t-1}$ | | | 0.000*** | | |
| | | | (4.54) | | |
| $OBS_{i,t-1}$*$Num\ of\ Branches_{i,t-1}$ | | | | 0.628*** | |
| | | | | (4.37) | |
| $OBS_{i,t-1}$* $M\&A\ events_{i,t-1}$ | | | | | 26.257* |
| | | | | | (1.96) |

| | | | | | |
|---|---|---|---|---|---|
| $CET1ratio_{i,t-1}$*$Non-interest\ income\ ratio_{i,t-1}$ | 0.000 | | | | |
| | (0.53) | | | | |
| $CET1ratio_{i,t-1}$*$NIS/NIM_{i,t-1}$ | | 0.026 | | | |
| | | (0.97) | | | |
| $CET1ratio_{i,t-1}$*$Num\ of\ employees_{i,t-1}$ | | | 0.000*** | | |
| | | | (3.25) | | |
| $CET1ratio_{i,t-1}$*$Num\ of\ Branches_{i,t-1}$ | | | | 0.004 | |
| | | | | (1.06) | |
| $CET1ratio_{i,t-1}$*$M\&A\ events_{i,t-1}$ | | | | | 0.354 |
| | | | | | (0.56) |
| $OBS_{i,t-1}$ | -3.801*** | -1.876*** | -2.728*** | -2.522*** | -1.863*** |
| | (-3.34) | (-2.87) | (-3.68) | (-3.63) | (-2.89) |
| $CET1ratio_{i,t-1}$ | -0.003 | 0.004 | -0.005 | -0.001 | 0.002 |
| | (-0.19) | (0.30) | (-0.41) | (-0.08) | (0.14) |
| $Non-interest\ income\ ratio_{i,t-1}$ | -0.003 | | | | |
| | (-0.84) | | | | |
| $NIS/NIM_{i,t-1}$ | | -0.669 | | | |
| | | (-1.01) | | | |

| | | | | | |
|---|---|---|---|---|---|
| $Num\ of\ employees_{i,t-1}$ | | | 0.000 | | |
| | | | (0.23) | | |
| $Num\ of\ Branche_{i,t-1}$ | | | | -0.070 | |
| | | | | (-1.34) | |
| $M\&A\ events_{i,t-1}$ | | | | | -3.864 |
| | | | | | (-0.58) |
| $\ln(total\ assets)_{i,t-1}$ | 0.947*** | 0.932*** | 0.848*** | 0.928*** | 0.944*** |
| | (11.60) | (10.81) | (10.01) | (11.54) | (11.51) |
| $Net\ loans\ to\ total\ asset_{i,t-1}$ | 0.008** | 0.008** | 0.006* | 0.007* | 0.007* |
| | (2.15) | (2.03) | (1.71) | (1.96) | (1.96) |
| $Cost\ to\ income_{i,t-1}$ | -0.004 | -0.003 | -0.006** | -0.004 | -0.004 |
| | (-1.15) | (-1.05) | (-2.05) | (-1.36) | (-1.25) |
| $Equity\ to\ assets_{i,t-1}$ | -0.006 | -0.006 | -0.010 | -0.008 | -0.009 |
| | (-0.37) | (-0.36) | (-0.60) | (-0.45) | (-0.53) |
| $ROA_{i,t-1}$ | -0.157*** | -0.156*** | -0.154*** | -0.149*** | -0.155*** |

| | | | | | |
|---|---|---|---|---|---|
| | (-4.76) | (-4.58) | (-4.53) | (-4.63) | (-4.57) |
| $GDP_{i,t-1}$ | -0.035*** | -0.034*** | -0.029*** | -0.031*** | -0.034*** |
| | (-5.91) | (-5.88) | (-4.75) | (-5.21) | (-5.79) |
| $CPI_{i,t-1}$ | -0.003 | -0.002 | -0.003 | -0.003 | -0.004 |
| | (-0.82) | (-0.55) | (-0.79) | (-0.74) | (-0.86) |
| *Constant* | -3.103* | -2.958* | -1.350 | -2.766* | -3.080* |
| | (-1.88) | (-1.75) | (-0.81) | (-1.73) | (-1.88) |
| *Bank FE* | YES | YES | YES | YES | YES |
| *Year FE* | YES | YES | YES | YES | YES |
| *Observations* | 3,641 | 3,640 | 3,473 | 3,641 | 3,641 |
| *R-squared* | 0.923 | 0.923 | 0.930 | 0.925 | 0.923 |

Note: This table reports the results for equation [3], which aims to assess the three-way interaction terms between the banks' shadow activities measure, various complexity measures and *CET1 ratio*. The dependent variable is *ln(NPL)*. Standard errors are clustered at the firm level, reported in parentheses below coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

The estimation results in Table 2.8 do not support the international capital market hypothesis. Many of the coefficients of interaction terms are statistically insignificant. In panel A of Table 2.8, the dependent variable is ln(NPL). All of Column (1) (2) (3) (4) and (5) show that the coefficient of the three-way interaction terms between off-balance item ratio, bank complexity measures and CET1 ratio are negative, suggesting that the marginal effect of bank complexity on the negative relationship between off balance sheet ratio and bank risk may be weaker with a higher CET1 ratio. Table 2.8, Panel B, which uses impaired loans to equity ratio as the dependent variable, also has similar insignificant results. These insignificant results may reflect statistical imprecision or opposing effects of the CET1 ratio on banks' realized risks. On one hand, high capitalization can provide capital buffers to banks. On the other hand, it is challenging to offset the agency costs and exposure to higher uncertainty in complex organizations. If banks cannot manage the risk, using the buffer may lead to more financial constraints when paying dividends. Therefore, the impact of high capital requirements on bank risks depends significantly on the level of risk exposure. Consequently, there remains uncertainty about whether the construction of an internal capital market, represented by capital adequacy, can moderate the impact of bank group complexity on risk through a portfolio rebalancing effect.

### 2.4.4.2 Agency problems

Other literature suggests that agency costs can moderate the relationship between business and organizational complexity and bank risk (Scharfstein & Stein, 2000). Agency costs may occur on two levels: unconscious and conscious. At the unconscious level, these costs arise from management difficulties faced by chief executives or boards. Initially, these difficulties reduce their ability to monitor risks effectively because they may lack the capability to manage complex situations, such as diverse business activities and redundant organizational structures, without appropriate experience (Hendry, 2005). Managing business complexity requires top management teams to possess compounded competence, which may conflict with specialization.

Limited alignment capabilities can hinder the alignment of new strategies with internal competencies due to a limited understanding of interrelationships among firm competencies related to product development (West & Anderson, 1996), resource bundles (Wooldridge, Schmid, & Floyd, 2008), and technology (Tyler, 2001). Organizational complexity is linked to greater information asymmetry and more hierarchical levels (e.g. Bens & Monahan, 2004; Demirkan & Demirkan, 2012; Duru & Reeb, 2002).

At the conscious level, there is the moral hazard problem, which is attributed to deliberate negligence. Agency theory assumes that both agents and principals are self-interested, and a moral problem arises when their interests diverge. This assumption suggests that bank agents in more complex institutions have incentives to take greater risks, even if not in the principals' best interest. By increasing business and organizational complexity and creating more tiers of information asymmetries, the deterrence of market discipline and regulations may be significantly diminished. This moral hazard leads to divisional rent seeking and less efficient investments by affiliates (Baule, 2014; Scharfstein & Stein, 2000).

Therefore, I focus on interaction terms to test whether the presence of agency problems can increase the marginal effect of bank complexity on banks' shadow activities and risk. I augment the baseline setup by interacting with the banks' shadow activities measures with agency problem measures. I estimate the following equation 4:

$$
\begin{aligned}
Risk_{it} = \delta_0 &+ \delta_1 BS_{i,t-1} + \delta_2 Complexity_{i,t-1} + \delta_3 TobinsQ_{i,t-1} \\
&+ \delta_4 Complexity_{i,t-1} * TobinsQ_{i,t-1} + \delta_5 TobinsQ * BS_{i,t-1} \\
&+ \delta_6 Complexity_{i,t-1} * BS_{i,t-1} + \delta_7 BS_{i,t-1} * Complexity_{i,t-1} \\
&* TobinQ_{i,t-1} \\
&+ \sum\nolimits_1^k Control_{i,t-1} + Macroecnomics_{c,t-1} + YearFE + BankFE \\
&+ \epsilon_{i,t}
\end{aligned}
$$

[4]

where $Risk_{it}$ is the matrices of risk measures. $BS_{i,t-1}$ is the banks' shadow activities measure. $Control_{k,t-1}$ is a set of bank-level control variables described in Section 3. $Macroecnomics_{c,t-1}$ represents control variables that measure the macroeconomic conditions and $\epsilon_{i,t}$ is the residual term. $\delta_7$ is the interest of coefficient, estimates of the interactions between the agency problem measure, the complexity measures and banks' shadow activities measures. The proxy of agent problem measure applied here is Tobin's Q ratio which is calculated by the market value of a company divided by its assets' replacement cost. This proxy has been widely used as the measure of agency problems since it was considered by Lang and Litzenberger (1989). What is more, $YearFE$ denotes year fixed effects accounting for global macroeconomic conditions affecting all bank groups to the same degree. $BankFE$ denotes that a bank fixed effects at the bank group level capturing unobserved firm-level characteristics. In all regression specifications, I cluster all standard errors at the bank level to allow errors correlated within banks among years.

**Table 2.10 (Panel A)** The effect of agency problem: Impaired loans to equity

| VARIABLES | (1) $Impaired\ loan\ to\ equity_{i,t}$ | (2) $Impaired\ loan\ to\ equity_{i,t}$ | (3) $Impaired\ loan\ to\ equity_{i,t}$ | (4) $Impaired\ loan\ to\ equity_{i,t}$ | (5) $Impaired\ loan\ to\ equity_{i,t}$ |
|---|---|---|---|---|---|
| $OBS_{i,t-1}$ $*$*$Tobins'Q_{i,t-1}$*$Non\ interest\ income\ ratio_{i,t-1}$ | -4.186* | | | | |
| | (-1.86) | | | | |
| $OBS_{i,t-1}$ $*$*$Tobins'Q_{i,t-1}$*$NIS/NIM_{i,t-1}$ | | -645.631*** | | | |
| | | (2.71) | | | |
| $OBS_{i,t-1}$ $*$*$Tobins'Q_{i,t-1}$*$Num\ of\ employees_{i,t-1}$ | | | 0.001 | | |
| | | | (0.86) | | |
| $OBS_{i,t-1}$ $*$*$Tobins'Q_{i,t-1}$*$Num\ of\ Branches_{i,t-1}$ | | | | 4.818 | |
| | | | | (0.24) | |
| $OBS_{i,t-1}$ $*$*$Tobins'Q_{i,t-1}$*$M\&A\ events_{i,t-1}$ | | | | | -2,412.010* |
| | | | | | (-1.90) |
| $OBS_{t-1}$ $*$*$Tobins'Q_{t-1}$ | 254.246** | 152.936** | 92.060 | 105.443 | 116.765* |
| | (2.46) | (2.07) | (1.20) | (1.51) | (1.73) |
| $OBS_{i,t-1}$* $Non-interest\ income\ ratio_{i,t-1}$ | 0.959** | | | | |

| | | | | | |
|---|---|---|---|---|---|
| | (2.18) | | | | |
| $OBS_{i,t-1}$*$NIS/NIM_{i,t-1}$ | | 123.240*** | | | |
| | | (-3.27) | | | |
| $OBS_{i,t-1}$* $Num\ of\ employees_{i,t-1}$ | | | 0.000 | | |
| | | | (0.72) | | |
| $OBS_{i,t-1}$*$Num\ of\ Branches_{i,t-1}$ | | | | 3.448 | |
| | | | | (1.64) | |
| $OBS_{i,t-1}$* $M\&A\ events_{i,t-1}$ | | | | | 474.761*** |
| | | | | | (2.67) |
| $Tobins'Q_{i,t-1}$*$Non-interest\ income\ ratio_{i,t-1}$ | 0.914* | | | | |
| | (1.92) | | | | |
| $Tobins'Q_{i,t-1}$*$NIS/NIM_{i,t-1}$ | | 34.718* | | | |
| | | (-1.82) | | | |
| $Tobins'Q_{i,t-1}$*$Num\ of\ employees_{i,t-1}$ | | | -0.001 | | |
| | | | (-1.54) | | |
| $Tobins'Q_{i,t-1}$*$Num\ of\ Branches_{i,t-1}$ | | | | -6.578 | |
| | | | | (-0.67) | |
| $Tobins'Q_{i,t-1}$*$M\&A\ events_{i,t-1}$ | | | | | 274.686 |
| | | | | | (0.90) |
| $OBS_{i,t-1}$ | -80.525*** | -63.064*** | -54.988*** | -53.173*** | -53.320*** |
| | (-3.53) | (-2.91) | (-2.62) | (-2.70) | (-2.66) |
| $Tobins'Q_{i,t-1}$ | -79.660*** | -56.419 | -39.079 | -42.509 | -48.483 |

| | | | | | |
|---|---|---|---|---|---|
| | (-3.81) | (-1.60) | (-1.09) | (-1.28) | (-1.44) |
| $Non\ interest\ income\ ratio_{i,t-1}$ | -0.172 | | | | |
| | (-1.56) | | | | |
| $NIS/NIM_{i,t-1}$ | | -7.133 | | | |
| | | (-0.88) | | | |
| $Num\ of\ employees_{i,t-1}$ | | | 0.000 | | |
| | | | (1.40) | | |
| $Num\ of\ Branches_{i,t-1}$ | | | | 1.127 | |
| | | | | (0.92) | |
| $M\&A\ events_{i,t-1}$ | | | | | -63.717* |
| | | | | | (-1.72) |
| $\ln(total\ assets)_{i,t-1}$ | 5.226*** | 4.802 | 3.663 | 4.490 | 4.687 |
| | (2.70) | (1.64) | (1.15) | (1.55) | (1.60) |
| $Net\ loans\ to\ total\ asset_{i,t-1}$ | 0.210** | 0.228** | 0.246** | 0.209* | 0.229** |
| | (2.42) | (2.14) | (2.20) | (1.91) | (2.13) |
| $Cost\ to\ income_{i,t-1}$ | -0.078 | -0.069 | -0.076 | -0.061 | -0.071 |
| | (-0.87) | (-0.55) | (-0.61) | (-0.50) | (-0.58) |
| $Equity\ to\ assets_{i,t-1}$ | 0.077 | 0.263 | 0.198 | 0.125 | 0.155 |
| | (0.22) | (0.51) | (0.37) | (0.25) | (0.30) |
| $ROA_{i,t-1}$ | -3.125* | -3.114* | -2.969* | -2.941 | -3.078* |
| | (-1.71) | (-1.73) | (-1.70) | (-1.65) | (-1.76) |
| $GDP_{i,t-1}$ | -0.392 | -0.342 | -0.353 | -0.387 | -0.387 |
| | (-1.49) | (-1.14) | (-1.06) | (-1.29) | (-1.28) |
| $CPI_{i,t-1}$ | 0.019 | -0.001 | 0.040 | 0.037 | 0.033 |
| | (0.30) | (-0.02) | (0.60) | (0.56) | (0.50) |
| *Constant* | -57.268 | -55.583 | -41.589 | -52.941 | -54.633 |
| | (-1.44) | (-0.99) | (-0.69) | (-0.95) | (-0.97) |
| *Bank FE* | YES | YES | YES | YES | YES |
| *Year FE* | YES | YES | YES | YES | YES |
| *Observations* | 3,383 | 3,382 | 3,247 | 3,383 | 3,383 |

| | | | | | |
|---|---|---|---|---|---|
| *R-squared* | 0.737 | 0.739 | 0.740 | 0.738 | 0.737 |

Note: This panel reports the results for equation [4], which aims to assess the three-way interaction terms between the banks' shadow activities measure, various complexity measures and *Tobin's Q*. The dependent variable is *Impaired loans to equity*.

**Table 2.9 (Panel B)** The effect of agency problems: ln(NPL)

| VARIABLES | (1)<br>$\ln(NPL)_{i,t}$ | (2)<br>$\ln(NPL)_{i,t}$ | (3)<br>$\ln(NPL)_{i,t}$ | (4)<br>$\ln(NPL)_{i,t}$ | (5)<br>$\ln(NPL)_{i,t}$ |
|---|---|---|---|---|---|
| $OBS_{i,t-1}$ **Tobins'*$Q_{i,t-1}$*<br>$Non\ interest\ income\ ratio_{i,t-1}$ | 0.022 | | | | |
| | (0.25) | | | | |
| $OBS_{i,t-1}$ *$Tobins'Q_{i,t-1}$*$NIS/NIM_{i,t-1}$ | | 14.089 | | | |
| | | (1.39) | | | |
| $OBS_{i,t-1}$*$Tobins'Q_{i,t-1}$*$Num\ of\ employees_{i,t-1}$ | | | -0.000* | | |
| | | | (0.18) | | |
| $OBS_{i,t-1}$*$Tobins'Q_{i,t-1}$*$Num\ of\ Branches_{i,t-1}$ | | | | -1.724* | |
| | | | | (-1.66) | |
| $OBS_{i,t-1}$ *$Tobins'Q_{i,t-1}$*$M\&A\ events_{i,t-1}$ | | | | | -48.445 |
| | | | | | (-0.99) |

| | | | | | |
|---|---|---|---|---|---|
| $OBS_{i,t-1}$ **$Tobins'Q_{i,t-1}$ | 0.904 | 3.590* | 2.401 | 4.400* | 2.574 |
| | (0.27) | (1.75) | (0.98) | (1.85) | (1.31) |
| $OBS_{i,t-1}$* $Non-interest\ income\ ratio_{i,t-1}$ | 0.008 | | | | |
| | (0.57) | | | | |
| $OBS_{i,t-1}$*$NIS/NIM_{i,t-1}$ | | -3.502*** | | | |
| | | (-2.98) | | | |
| $OBS_{i,t-1}$* $Num\ of\ employees_{i,t-1}$ | | | 0.000*** | | |
| | | | (4.19) | | |
| $OBS_{t-1}$*$Num\ of\ Branches_{i,t-1}$ | | | | 0.458*** | |
| | | | | (4.71) | |
| $OBS_{i,t-1}$* $M\&A\ events_{i,t-1}$ | | | | | 9.699* |
| | | | | | (1.80) |
| $Tobins'Q_{i,t-1}$*$Non-interest\ income\ ratio_{i,t-1}$ | -0.021 | | | | |
| | (-0.91) | | | | |
| $Tobins'Q_{i,t-1}$*$NIS/NIM_{i,t-1}$ | | -1.158 | | | |
| | | (-0.99) | | | |
| $Tobins'Q_{i,t-1}$*$Num\ of\ employees_{i,t-1}$ | | | 0.000 | | |
| | | | (0.12) | | |

| | | | | | |
|---|---|---|---|---|---|
| $Tobins'Q_{i,t-1}*Num\ of\ Branches_{i,t-1}$ | | | | 0.767* | |
| | | | | (1.66) | |
| $Tobins'Q_{i,t-1}*M\&A\ events_{i,t-1}$ | | | | | -7.966 |
| | | | | | (-0.52) |
| $OBS_{i,t-1}$ | -1.476*** | -1.689*** | -1.845*** | -1.852*** | -1.390*** |
| | (-2.78) | (-3.79) | (-4.08) | (-4.40) | (-3.14) |
| $Tobins'Q_{i,t-1}$ | -1.819** | -2.874*** | -2.933*** | -3.272*** | -2.714*** |
| | (-2.23) | (-3.71) | (-3.39) | (-3.77) | (-3.64) |
| $Non\ interest\ income\ ratio_{i,t-1}$ | 0.003 | | | | |
| | (0.77) | | | | |
| $NIS/NIM_{i,t-1}$ | | -0.298 | | | |
| | | (-0.91) | | | |
| $Num\ of\ employees_{i,t-1}$ | | | 0.000 | | |
| | | | (1.29) | | |
| $Num\ of\ Branches_{i,t-1}$ | | | | -0.060* | |

| | | | | | |
|---|---|---|---|---|---|
| | | | | (-1.74) | |
| $M\&A\ events_{i,t-1}$ | | | | | 0.301 |
| | | | | | (0.20) |
| $\ln(total\ assets)_{i,t-1}$ | 0.910*** | 0.914*** | 0.848*** | 0.908*** | 0.914*** |
| | (15.85) | (9.96) | (9.14) | (10.54) | (10.32) |
| $Net\ loans\ to\ total\ asset_{i,t-1}$ | 0.012*** | 0.013*** | 0.013*** | 0.012*** | 0.013*** |
| | (4.52) | (3.49) | (3.56) | (3.33) | (3.48) |
| $Cost\ to\ income_{i,t-1}$ | -0.005** | -0.005* | -0.006* | -0.005* | -0.006* |
| | (-2.34) | (-1.68) | (-1.92) | (-1.83) | (-1.92) |
| $Equity\ to\ assets_{i,t-1}$ | 0.024** | 0.026* | 0.022 | 0.021 | 0.021 |
| | (2.02) | (1.65) | (1.34) | (1.30) | (1.27) |
| $ROA_{i,t-1}$ | -0.158*** | -0.159*** | -0.151*** | -0.158*** | -0.157*** |
| | (-5.55) | (-4.76) | (-4.78) | (-4.79) | (-4.77) |
| $GDP_{i,t-1}$ | -0.034*** | -0.031*** | -0.032*** | -0.032*** | -0.033*** |

| | | | | | |
|---|---|---|---|---|---|
| | (-6.01) | (-4.78) | (-4.64) | (-4.88) | (-5.02) |
| $CPI_{i,t-1}$ | -0.001 | -0.002 | -0.001 | -0.001 | -0.001 |
| | (-0.29) | (-0.61) | (-0.35) | (-0.35) | (-0.43) |
| *Constant* | -2.944*** | -2.928 | -1.841 | -2.714 | -2.832 |
| | (-2.63) | (-1.63) | (-1.01) | (-1.58) | (-1.61) |
| *Bank FE* | YES | YES | YES | YES | YES |
| *Year FE* | YES | YES | YES | YES | YES |
| *Observations* | 3,353 | 3,352 | 3,217 | 3,353 | 3,353 |
| *R-squared* | 0.930 | 0.930 | 0.932 | 0.931 | 0.930 |

Note: This panel reports the results for equation [4], which aims to assess the three-way interaction terms between the banks' shadow activities measure, various complexity measures and *Tobin's Q*. The dependent variable is *ln(NPL).* Standard errors are clustered at the firm level, reported in parentheses below coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Overall, the evidence for the agency problem hypothesis in both business and organizational complexity dimensions is inconclusive. Some of the three-way interaction terms show statistical significance for *Impaired loans to equity ratio* concerning business complexity measures like *non-interest income ratio* and *NIS/NIM* ratio (Columns 1 and 2 in Table 2.9 Panel A). There are also indications of the agency problem in the dimension of organizational complexity affecting *ln(NPL)*, particularly concerning *number of employees* and *number of branches* (Columns 3 and 4 in Table 2.9 Panel B). While these findings somewhat align with the conjecture that the agency problem within bank group management could potentially heighten the bank risk arising from shadow activities through business and organizational complexity, they are not consistent estimations. In general, monitoring efforts aimed at mitigating the agency problem appear to have a dampening effect on the impact of riskiness induced by banks' shadow activities within the bank group. However, it is important to acknowledge that the limited availability of data hinders achieving statistical significance for some results.

## 2.5. Conclusion

This study aims to investigate the relationship between banks' shadow activities and their idiosyncratic realized risk, further enriching the discourse on risk management within the banking sector. Through comprehensive empirical analyses, the research reveals that banks engaging in more pronounced shadow activities generally exhibit lower realized risks compared to their less shadowed counterparts. This finding underscores the intricate dynamics that shadow banking introduces to traditional risk frameworks.

A particularly novel aspect of this research is the exploration of the role of bank complexity. By dissecting the impact of both business and organizational complexity, the study demonstrates that these elements can attenuate the otherwise negative association between banks' shadow activities and risk. This suggests that as banks grow in complexity, the risk-mitigating benefits of shadow activities engagement diminish, exposing them to potentially heightened vulnerabilities. Additionally, this research indicates that internal capital markets and improved management practices are insufficient to counteract the moderating effects of bank complexity on this relationship. These insights highlight the importance of understanding context-specific factors such as complexity.

The research highlights the need for tailored regulatory oversight and risk management strategies from policymakers and banking regulators. Regulatory frameworks shall evolve to take into account the unique characteristics of shadow-involved banks and their specific risk profiles, ensuring that oversight is both flexible and well-informed by the realities of modern banking.

# Chapter 3
# Banks' Fintech adoption: How does it relate to banks' risk and shadow activities?

## 3.1. Introduction

Fintech (financial technology), which integrates information technology with financial services, has become increasingly prevalent in recent years. The rapid advancement of Fintech has led to its wide application in lending, payment systems, financial advising, and insurance. Global transaction revenue driven by Fintech has increased from $234.73 billion in 2017 to $3.3 trillion in 2022, and it is estimated to reach $9.2 trillion by 2027 (Statista, 2025). This growth has sparked intense debate regarding the overall benefits and drawbacks it brings to the financial industry, especially amid ongoing uncertainty about how and to what extent this sector should be regulated.

Traditional banks are often overlooked in Fintech discussions (Thakor, 2020). Fintech 3.0, characterized by the rise of big tech companies and innovative Fintech startups, marks a significant departure from earlier stages, Fintech 1.0 and 2.0. Unlike its predecessors, Fintech 3.0 is often seen as a disruptive force challenging the traditional dominance of banks in financial intermediation. Many traditional banking advantages, such as customer base and franchise value, are vulnerable to advancements in digital technology and big data. Banks embracing the Fintech trend can derive substantial benefits such as enhanced operational efficiency (Boot, 2016; Elia, Stefanelli, & Ferilli, 2023; Karim & Lucey, 2024), cost savings, expanded service offerings, and ultimately, increased profitability ( Kayed, Alta'any, Meqbel, Khatatbeh, & Mahafzah, 2024; Lee, Li, Yu, & Zhao, 2021; Tarawneh, Abdul-Rahman, Mohd Amin, & Ghazali, 2024). However, the impact of Fintech on bank risk remains a subject of debate, with existing studies reporting mixed results.

On the one hand, Fintech may increase the level of bank risk (e.g., Croux, Jagtiani, Korivi, & Vulanovic, 2020; Wang, Mao, Wu, & Luo, 2023a). First, substantial investments in Fintech infrastructure can drive up operational costs, erode profits, and raise the bank's exposure to default risks. Second, competitive pressure from agile Fintech startups and high-tech firms may force traditional banks into costly innovation efforts, potentially pushing them toward riskier strategies that could reduce profitability. Finally, incorporating new digital technologies introduces significant cybersecurity threats, including cyberattacks and data breaches, which can disrupt operations and heighten vulnerabilities.

On the other hand, Fintech may decrease the level of bank risk (e.g., Holland, Lockett, & Blackman, 1997; Albastaki, Razzaque, & Sarea, 2020; Heo, 2023). Fintech can enhance bank stability by improving operational efficiency and decision-making processes, leading to higher returns. Advanced analytics, such as machine learning, helps banks understand customers better, reduce transaction costs, and support credit risk management. Fintech-powered regulatory technology (RegTech) offers automated compliance solutions, enabling banks to proactively manage regulatory changes and optimize portfolios. This technological integration may result in lower default risks, reduced earnings volatility, and higher risk-adjusted returns. Overall, Fintech presents both opportunities and challenges for banks, influencing their risk levels.

Fintech can also influence the level of banks' shadow activities, representing a critical yet understudied area of transformation. These opaque financial practices have historically received limited scrutiny from regulators and researchers. Fintech introduces a transformative element into this landscape, necessitating a reevaluation of existing financial intermediation theories concerning bank risk and shadow banking (Stulz, 2019). Hypothetically, Fintech may increase the level of banks' shadow activities. It facilitates innovative shadow activities by enabling banks to collaborate with Fintech startups and establish subsidiaries, thereby exploiting regulatory arbitrage opportunities.

Moreover, advanced encryption and data obfuscation technologies in Fintech can hinder regulatory oversight, complicating the detection of fraudulent activities and compliance assurance.

It can also be hypothesized that as banks increase their shadow activities, the negative relationship between Fintech and bank risk becomes less pronounced. While Fintech and shadow activities can independently reduce risk, their combination may introduce complexity and interconnectedness, potentially raising overall risk. When banks engage in shadow banking activities through Fintech channels—whether by adopting Fintech solutions, partnering with Fintech startups, or investing in Fintech platforms—they may be inclined to tap into riskier segments of borrowers. This occurs because Fintech solutions often provide access to a broader market that traditional banks may otherwise avoid, capturing higher-yield opportunities in exchange for greater risk exposure. Additionally, cross-jurisdiction regulatory gaps resulting from Fintech adoption can obscure financial transactions, leading to increased risk-taking.

This paper aims to examine the implications of Fintech for banks through the unique lens of banks' shadow activities and bank risk management. Specifically, I focus on three questions: First, what is the empirical relationship between Fintech and bank risk? Second, what is the empirical relationship between Fintech and banks' shadow activities? Third, how does Fintech affect the relationship between banks' shadow activities and bank risk? Most similar studies focus on a single or regional market (Carlini, Del Gaudio, Porzio, & Previtali, 2022; Lee, Ni, & Zhang, 2023; Wang, Huang, Gu, Song, & Sun, 2023b; Wu, Jin, Yang, & Qi, 2023). In this study, I use a worldwide sample of up to 359 of the largest bank groups during the period 2008-2022. Using global data helps address theoretical concerns by including a variety of economic conditions, regulatory frameworks, cultural and institutional environments, and financial market structures. This diversity ensures that findings are robust and applicable across different contexts, enhancing the generalizability and credibility of the theory. The post-2008 dataset is more relevant for understanding the contemporary landscape of shadow banking, allowing me to capture developments and trends that have occurred in the aftermath of the financial crisis.

The key explanatory variable is "Fintech," a term with no standard definition and unclear boundaries, leading to a lack of consensus on measurement. To address this challenge, many studies develop a Fintech development index and use Ordinary Least Squares (OLS) regression for analysis (e.g. Dong & Yu, 2023; Wu, Pathan, & Zheng, 2024). However, these indexes often capture only the technological aspects of Fintech in banks, overlooking conscious and strategic factors of Fintech adoption that are difficult to observe and measure (Le, Ngo, Nguyen, & Do, 2024; Murinde, Rizopoulos, & Zachariadis, 2022). To tackle this issue, I propose using "Fintech 3.0" as a proxy measure and treatment variable. I employ a staggered Difference-in-Differences (DID) approach, a quasi-experimental design that helps establish causal relationships between an intervention (Fintech) and its impact on banks' shadow activities and risk profiles. During the sample period, banks varied in their adoption of Fintech 3.0. The DID method allows for estimating the treatment effect of Fintech by comparing changes over time between a group that receives the treatment and a control group that does not. This approach enables the inclusion of unobserved impacts of Fintech. To identify when keywords like "Fintech" were first introduced to the selected bank group, I manually retrieved the year of their first appearance in annual reports. In relevant cases, I performed placebo tests to rule out the influence of other competing factors and conducted parallel trend tests to ensure the robustness of the analysis.

This chapter has three findings. First, banks engaging in Fintech exhibit lower realized risk on average, as indicated by metrics such as impaired loans loss ratio, non-performing loan ratio, and loan loss provision ratio. These findings align with those from other studies using different methodologies (Cheng & Qu, 2020; Li, Elahi, & Zhao, 2022; Li, Li, Zhu, Yao, & Casu, 2020; Wang, Liu, & Luo, 2021). Second, Fintech may boost banks' engagement in shadow activities, although this effect can be insignificant. Notably, banks that are more involved in investment activities tend to increase their shadow activities following Fintech adoption. Third, banks' shadow activities facilitated by Fintech can elevate bank risk. The negative relationship between Fintech and bank risk is weakened when banks engage in shadow activities.

This research aims to unravel the complex relationship between Fintech, bank risk and banks' shadow activities, making two key contributions to the existing literature. First, this study provides more comprehensive insights into the impact of digitalization on the banking sector. While previous studies have offered valuable perspectives on digitalization trends in banks, they often do not address the most relevant stage of Fintech evolution (e.g. Chen et al., 2015; Ha, 2022). This paper specifically focuses on "Fintech 3.0," a stage uniquely relevant to the current landscape of Fintech development and most disruptive to the traditional banking industry. By employing an innovative Difference-in-Differences (DID) model that uses Fintech as a signaling indicator, the research aims to capture the radical transformation and unobservable factors that Fintech introduces to the traditional banking industry. This approach allows for historical and cross-sectional analysis, providing a deeper understanding of Fintech's transformative impact beyond incremental changes.

Second, this paper contributes to the literature by examining the causality between Fintech and bank risk, particularly within the context of shadow banking activities. The role and functions of shadow banking have been undergoing substantial shifts in recent years, impacting the broader economy. Understanding these changes is crucial for ensuring overall financial stability, a topic that deserves increased attention. Unlike other studies that focus on how Fintech influences shadow banking systems outside the traditional banking framework (Buchak et al., 2018; Zhang, Que, & Qin, 2023), this research offers a novel perspective by analyzing the evolving dynamics within the banking sector. It explores whether Fintech is transforming the extent of shadow banking within traditional banking institutions and the associated risks (Molnár, 2018). In future research, this exploration can serve as a foundation for delving into the broader implications of Fintech for the financial ecosystem, including the stability of financial markets and the protection of consumers.

This chapter has six sections. Section 1 is an introduction. Section 2 shows the background. Section 3 presents hypotheses development process. Section 4 details the sample data and variables employed in the empirical tests. Section 5 presents empirical results and findings. Section 6 concludes the chapter.

## 3.2. Background

### 3.2.1. Fintech

Fintech has driven disruptive changes that have fundamentally reshaped market definitions, operations, and business models within the financial sector (An & Rau, 2021). As a pivotal force, Fintech plays an increasingly essential role in shaping strategic decision-making processes and operational frameworks. Characterized by the innovative use of information and automation technology in financial services, Fintech has given rise to a new generation of both front and back-office systems. These systems are built on components such as databases, data mining tools, data analytics tools, and application programming interfaces (APIs). Through these components, Fintech enables informed, automated decisions and facilitates the seamless exchange of data, events, and services both within and beyond the enterprise (Puschmann, 2017).

### 3.2.2. The stages of Fintech

In retrospect, the evolution of Fintech can be divided into three stages. ‘Fintech 1.0’ dates back to the mid-19th century, when technological inventions and infrastructure began supporting globalized financial services. Notable developments include the first transatlantic cable in 1866 and Fedwire in 1918, which enabled the first electronic fund transfer system in the USA. Although simple by today's standards, these innovations revolutionized long-distance financial transactions at the time. ‘Fintech 2.0’ began in the 1960s, marked by the shift from analog to digital finance. This era saw the emergence of technologies such as digital stock exchanges, SWIFT, online banking, and digital banking (Giglio, 2022).

Fintech 3.0 (2008-present) represents a significant phase in the financial industry, driven by Fintech startups, innovative providers, and decentralized finance. This stage has brought transformative changes across several dimensions. First, it emphasizes technologies like artificial intelligence, big data, and cloud computing, revolutionizing the financial landscape through automation, enhanced data-driven decision-making, and personalized services. Second, Fintech 3.0 is characterized by decentralized business models, fostering open banking and platform-oriented ecosystems. This environment demands collaboration and strategic partnerships between banks and other financial service providers to navigate the rapidly evolving market effectively. Third, this stage involves significant changes in competitive and regulatory environments. Fintech startups challenge traditional institutions, prompting continuous innovation and adaptation to new market demands. Meanwhile, the regulatory landscape evolves, with updates to compliance frameworks to integrate new technologies safely. For example, the Financial Data Access Directive (FiDA) in the EU standardizes rules for data sharing, accessibility, and security, balancing innovation with consumer protection and financial stability (Elia et al., 2023; Giglio, 2022; Jalal, Al Mubarak, & Durani, 2023; Nair and Gallo, 2024).

While the concept of ‘Fintech’ encompasses all three stages, this paper focuses specifically on Fintech 3.0 for several reasons. First, Fintech 3.0 represents the current stage of evolution, aligning closely with common parlance and capturing the essence of contemporary Fintech, making it particularly relevant for analysis. Second, unlike earlier stages, Fintech 3.0 marks a leadership shift from traditional banks to innovative

Fintech startups, positioning banks as followers. This stage signifies a disruptive transformation not only in technology but also in the strategic and operational levels of traditional banking. Banks must rethink their competitive strategies and focus on digital transformation and agile methodologies to respond to the disruptive potential of Fintech startups. This strategic evolution is necessary for banks to maintain their market positions and leverage the opportunities presented by Fintech 3.0, despite the challenges it poses.

## 3.3. Literature review and hypotheses development

Recent literature explores the transformative impact of Fintech on the banking sector, highlighting both opportunities and challenges. Boot (2016) provides an early analysis, suggesting that Fintech innovation is reshaping traditional banking by enhancing efficiency. The study emphasizes how technological advancements in payment systems, lending, and personal finance management are forcing banks to adapt their business models to stay competitive. Elia, Stefanelli, & Ferilli (2023) further show that traditional banks are compelled to invest in digital transformation due to the structural changes in the banking industry prompted by Fintech. Karim & Lucey (2024) also focus on the competitive dynamics between banks and Fintech startups. They note that while Fintech firms initially posed a threat to traditional banks, collaboration has become a more common strategy. Partnerships between banks and Fintech startups allow banks to leverage cutting-edge technology while maintaining their established customer base, ultimately enhancing financial inclusivity and innovation. Kayed et al. (2024) examine the regulatory implications of Fintech's rise. They highlight the need for updated regulatory frameworks that accommodate the unique challenges posed by Fintech. Banks are encouraged to work closely with regulators to ensure compliance while fostering innovation. Lee et al. (2021) provide insights into the consumer perspective, emphasizing how Fintech applications have increased accessibility to financial services. This shift has pressured banks to enhance their digital interfaces and offer more personalized services.

Some studies focus on how Fintech influences banks' risk (Hu, Zhao & Yang 2024; Carlini et al., 2022; Hu, Zhao, & Yang, 2024; Lee et al., 2023; Marcelin, Sun, Teclezion, & Junarsin, 2022; Wang et al., 2023b; Wu et al., 2023). However, most of the existing literature focuses on regional markets and does not distinguish the stages of Fintech development, with inconsistencies in the results. Moreover, despite the focus on the relationship between Fintech and bank risk, there is a notable lack of analysis on how this relationship varies in the context of banks' shadow activities.

The advanced structure of the system enabled by Fintech 3.0 could potentially lead to a decrease in bank risk. The reasons are mainly three ways. Firstly, it improves bank stability. Using Fintech solutions to replace operating and decision-making process, banks may see an increase in operational efficiency and marginal return (Hasan, Hoque, & Le, 2023). Secondly, it improves banks' understandings towards their customers and investors. Applying machine learning, deep learning and other analytic techniques, banks are capable of marketing precisely based on the comprehensive user portrait, which reduces banks' transaction costs, more importantly, allowing them to adapt to all kinds of financial scenarios and meet various financial needs (Koeplin & Lélé, 2023). Specifically, in a scenario of loan transactions, by conducting a comprehensive 360-degree view of customers, an in-depth and objective data analysis could be provided, supporting credit risk management and increasing financial safety (Croux, Jagtiani, Korivi, & Vulanovic, 2020; Wang, Mao, Wu, & Luo, 2023a). Thirdly, it improves banks' ability to response to the financial market and regulation shocks. Fintech-powered regulatory technology (RegTech) offers automated solutions for compliance (Omarova, 2020). These tools assist banks in streamlining regulatory reporting, monitoring transactions for suspicious activities, and ensuring adherence to intricate regulatory requirements. Relying on the data governance framework, banks enable to obtain comprehensive senses of market and detect subtle changes in supervision landscape, helping with regulatory compliance and portfolio optimization (Karkošková, 2023). In this way, instead of grappling with emergencies, banks could take proactive actions to prevent risks. In general, equipped with Fintech 3.0, banks may have lower default risk, lower earnings volatility and higher risk-adjusted returns. Therefore, I make the following hypothesis.

*H1a: Fintech adoption is associated with a deduction in bank risk.*

At the same time, Fintech presents significant challenges to traditional banks which potentially increase risk (Holland, Lockett, & Blackman, 1997). Firstly, the total expense of building Fintech architecture is substantial, and it may take a considerable amount of time before the appropriate scale of Fintech infrastructure can function effectively and generate sustained advantages. Especially in the early stages of the construction cycle, banks may find that their investment conversion rates are relatively low in the short term. These factors could increase operational costs and erode profits, thereby raising the risk of default. Moreover, the development of Fintech may place traditional banks in an aggressive competitive landscape where they are inherently disadvantaged, leading to overinvestment and risk-taking. This is due to the disruptive effect of Fintech on traditional banking, as the most cutting-edge informational technologies and concepts are typically controlled by prominent high-tech companies such as Apple, Google, Alibaba, and Tencent, which have shown significant interest in financial services in recent years. The pressure to compete in the Fintech arena may prompt banks to engage in irrational upgrading and innovation, which can decrease profits and increase the motivation to take risks (Albastaki, Razzaque, & Sarea, 2020). Additionally, the complexity of integrating new technologies into Fintech 3.0 can introduce default risks into the banking system. Heo (2023) highlights that cybersecurity threats, such as cyberattacks and data breaches, have the potential to lead to bank defaults and fragility. Najaf, Mostafiz, & Najaf (2021) demonstrate that banks deeply involved in Fintech may be vulnerable to malware attacks on their payment systems, exposing them to cyber fraud. Therefore, the following hypothesis below is speculated.

*H1b: Fintech adoption is associated with an increase in bank risk.*

Entering the realm of Fintech 3.0 could potentially lead to an increase in banks' shadow activities. Firstly, Fintech facilitates innovative shadow activities by enabling banks to collaborate with Fintech startups and form FinTech subsidiaries. These collaborations allow banks to exploit regulatory arbitrage opportunities. For instance, banks can leverage Fintech startups to participate in P2P lending platforms which are often subject to less stringent regulations compared to traditional banks. As a result, banks gain more market share in the lending market without being burdened by the same regulatory constraints (Chen & Bellavitis, 2020). Secondly, Fintech enhances banks' ability to escape from regulatory discipline, creating challenges for regulations and supervision in shadow banking activities (González-Páramo, 2017). Atadoga et al. (2024) indicate that advanced encryption and data obfuscation techniques, widely applied in Fintech to protect customer data, can also make it difficult for regulators to access and analyze the data needed for oversight. This can hinder regulatory efforts to detect fraudulent activities and ensure compliance. Particularly, the use of blockchain technology and smart contracts in Fintech can create opaque transactions that are challenging for regulators to monitor and control. Therefore, I compose the following hypothesis:

*H2: Fintech adoption contributes to an increase in banks' shadow activities.*

In order to further understand the heterogeneity behind the relationship between banks' shadow activities, Fintech and bank risk, the third test discusses whether the correlation between Fintech and bank risk may vary due to the impact of banks' shadow activities.

The combination of Fintech and banks' shadow activities might introduce complexity and interconnectedness that increase overall bank risk. Research by Bao & Huang (2021) highlights that Fintech startups, particularly in China, have expanded credit access to new and financially uncertain borrowers, especially after the COVID-19 pandemic. This has resulted in high delinquency rates and increased fragility of lending institutions. When banks engage in shadow activities through FinTech, they may target underserved groups with higher risk profiles to gain more loan market share, inadvertently increasing the banks' overall risk exposure (Al-Ajlouni, 2018). Also, one typical combination of Fintech and banks' shadow activities is banks investing in Fintech startups and digital platforms to circumvent regulatory limits. The connection between banks and Fintech startups can lead to contagion risks, where financial distress in Fintech startups quickly spreads to banks which increases bank risk. The use of Fintech in banks' shadow activities might make it harder for regulators to oversee shadow banking activities (Bromberg, Godwin, & Ramsay, 2017; Hodula & Ngo, 2024). For example, banks' shadow activities combined with Fintech often take advantage of differences in regulatory requirements across jurisdictions, further obscuring the origins and nature of financial transactions. This can lead to regulatory gaps and to increased bank risk-taking. Given that, I expect that:

*H3: The increase in banks' shadow activities weaken the negative relationship between Fintech adoption and bank risk.*

## 3.4. Sample, data and variables

The primary sample includes bank groups with detailed bank-level financial data from the Bureau van Dijk BankFocus database, covering the fiscal years 2008 to 2021. This period is particularly relevant because the issue of "banks' shadow activities" first emerged as a common concern among researchers and policymakers. It encompasses significant changes in the global banking system that influence these shadow activities, making it especially suitable for analysis.

The examination of banks' shadow activities is focused on the ultimate group company level, where crucial business strategy decisions, such as engaging in shadow banking activities, are typically made. By studying the highest holder level, I aim to attain a comprehensive understanding of the overall impact of banks' shadow activities on the entire bank group. To ensure the representativeness and availability of the dataset, a minimum threshold of US$15 million on the total asset scale was established. This criterion was employed to ensure that the selected banks are of sufficient size and significance to accurately capture their influence on the banking sector (Cole & White, 2012). Finally, this sample set comprises an unbalanced panel of annual financial data obtained from up to 359 of the world's largest bank groups. However, the number of banks included may vary from year to year, resulting in a total of up to 4565 bank-year data points.

### 3.4.1. Measurement of Fintech 3.0

Since there is no universal definition of Fintech 3.0, measuring its impact on different bank groups is challenging. Many studies address this by constructing a Fintech-related lexicon from text sources like news articles or annual reports (e.g. Dong and Yu 2023; Wu, Pathan, & Zheng, 2024). However, this approach often emphasizes technological aspects, potentially overlooking deeper, strategic implications that are difficult to measure and observe. To address this issue, I conduct an index search using selected Fintech-related narratives as indicators of Fintech 3.0. This approach aims to identify when "Fintech 3.0" was recognized and introduced to the sampled banks.

Specifically, I manually identify the year the keyword "Fintech" first appeared in their annual reports, using this as a treatment variable. If "Fintech" was not mentioned, I search for related terms like "artificial intelligence" and "machine learning" as alternative indicators.

The choice of "Fintech" as an indicator of Fintech 3.0 realization is based on two reasons. First, the concept of Fintech has appeared in the annual reports of sampled bank groups since 2014, aligning with the era of Fintech 3.0. Hence, it is reasonable to assume that "Fintech" specifically refers to Fintech 3.0 within the banking industry. Second, Fintech-related narratives in annual reports are symbolically significant for bank groups. These reports aim to provide investors with critical information to guide investment decisions, reflecting key business strategies and the company's future direction.

The explicit mention of "Fintech" in these reports indicates two significant transformations within bank groups. First, it signals strategic awareness of the profound changes in the competitive landscape brought about by Fintech 3.0. Recognizing this new financial paradigm, where burgeoning Fintech startups challenge traditional bank roles, helps bank groups develop crisis awareness and foster proactive responses. Second, it encourages bank groups to explore integrating technology-enabled financial innovations into their practices. This trend, evident at the decision-making level, leads to increased reliance on Fintech as bank groups formulate operational, investment, and expansion strategies.

I have chosen "artificial intelligence" and "machine learning" as alternative indicators of the inception of Fintech 3.0, rather than other technologies associated with this phase, for two key reasons. First, "artificial intelligence" and "machine learning" are among the most representative solutions in the rapidly evolving landscape of Fintech 3.0, where the pace of technological advancements leads to a high turnover of innovations. These technologies effectively signify a shift towards more sophisticated, data-driven approaches, reflecting bank groups' commitment to embracing Fintech 3.0. Additionally, they serve as indicators of whether these institutions are progressing in the right direction regarding technological adoption.

Second, artificial intelligence and machine learning are central components of Fintech 3.0, closely interacting with other key technologies such as cloud computing and big data. For instance, artificial intelligence leverages big data to train its algorithms by analyzing vast datasets that include customer transactions, behavioral patterns, and market trends. This analysis enables AI systems to identify patterns, make predictions, and improve decision-making processes. Meanwhile, cloud computing provides the essential infrastructure that supports these technologies by offering scalable storage and processing power (Cao, Yang, & Yu, 2021; Cao, Yuan, Leung, & Zhang, 2020).

### 3.4.2. Measurement of banks' shadow activities

The proxy of banks' shadow activities is the off-balance sheet ratio which is calculated as off-balance sheet items divided by total on and off-balance sheet exposures. Bank groups are increasingly involved in off-balance sheet activities as a part of attempt in financial innovation. Off-balance sheet activities comprise a volume of non-traditional banking activities that are out of regulation supervision, such as asset management service, securitization, derivatives trading, special purpose entities, guarantee, commitments and other transactions, representing a considering level of banks' shadow activities. A higher off-balance sheet ratio suggests greater reliance on off-balance sheet activities, indicating a potentially larger presence of banks' shadow operations.

### 3.4.3. Measurement of bank risk

The risk indicators used in this paper are non-performing loan ratio, impaired loans to equity ratio and loan loss provision ratio. All of these three measures portray the asset quality of bank groups: a higher value of these three measures means that there is a great chance that bank groups have a problem with recalling their outstanding loans due to the default of their borrowers. Therefore, an increase of Non-performance loan ratio, impaired loans to equity ratio and loan loss provision ratio are directly related to the increase in credit risk, liquidation risk and default risk of banks (Bushman & Williams, 2012; Wang et al., 2023a).

### 3.4.4. Control variables

In all estimations I include a vector of variables to control for time-varying bank-specific characteristics that are other determinants of risk commonly employed in the literature (e.g. Goetz et al. 2013, Jiang et al. 2017, Ly et al. 2018). I control for the following bank-specific variables: bank size (natural log of total assets), business model (loan-to-assets ratio), earnings (return on assets), management quality (cost-to-income ratio), financial leverage (equity-to-assets ratio), and bank profitability (ROA). To control country-level macro conditions, I use annual real GDP growth rate and core CPI growth rate which are collected from World Bank database.

### 3.4.5. Descriptive statistics

Table 3.1 presents a comparison of key statistics between the treatment group (those with Fintech) and the control group (those without Fintech). On average, banks in the treatment group hold approximately 20.7% of off-balance sheet items as a proportion of their total on and off-balance sheet exposure. There is notable variation among banks, with the highest off-balance sheet items ratio reaching around 80%. In contrast, banks in the control group have an average off-balance sheet items ratio of 21%.

Examining other metrics, the average impaired loans to equity ratio is 19% for the treatment group and 25% for the control group. The non-performing loan ratio averages 3.02% in the treatment group and 3.7% in the control group. Lastly, the average loan loss provision ratio is 20.1% for the treatment group and 20.9% for the control group. Notably, there are no significant differences in the means of these fundamental data points between the two groups. However, it's worth mentioning that the standard deviations are smaller in the treatment group.

**Table 3.1:** Descriptive Statistics

| Variables | Without Fintech | | | | With Fintech | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Min | Max | Mean | Std. Dev. | Min | Max |
| Off Balance sheet item ratio (OBS) | 21.054 | 15.143 | 0 | 97.923 | 20.745 | 14.675 | 0 | 90.612 |
| Impaired loans to equity | 24.982 | 40.049 | -0.610 | 257.570 | 18.982 | 28.403 | -0.160 | 257.570 |
| Non-Perf Loan ratio | 3.744 | 5.281 | -0.040 | 32.96 | 3.026 | 4.108 | -0.040 | 32.960 |
| Loan Loss Prov ratio | 20.917 | 25.24 | -27.200 | 143.300 | 20.125 | 22.312 | -27.200 | 143.300 |
| ln total assets | 17.584 | 1.532 | 14.845 | 21.697 | 18.534 | 1.461 | 15.356 | 21.697 |
| Net Loan to Total asset | 57.107 | 15.846 | 3.99 | 85.22 | 55.38 | 15.288 | 3.99 | 85.22 |
| Cost to income | 55.905 | 16.005 | 23.05 | 112.17 | 52.827 | 15.329 | 23.05 | 112.17 |
| Equity to assets | 10.106 | 4.682 | 2.820 | 38.07 | 9.862 | 4.105 | 3.71 | 38.07 |
| ROA | 0.419 | 0.613 | 0.015 | 4.011 | 0.376 | 0.594 | 0.015 | 4.011 |
| GDP growth | 2.769 | 3.413 | -25.908 | 15.836 | 2.167 | 4.278 | -25.908 | 11.737 |
| CPI | 2.986 | 4.273 | -4.863 | 154.756 | 2.63 | 6.46 | -2.54 | 154.756 |

Note: This table contains descriptive statistics of key variables, comparing banks with Fintech to those without. I provide a detailed definition of each variable in Appendix B1. I winsorize all continuous control variables at the 1st and 99th percentiles.

## 3.5. Empirical analysis

### 3.5.1. The relationship between Fintech and bank risk

In this section, I test Hypothesis 1 whether bank risk is attenuated by the adoption of Fintech 3.0. Specifically, I estimate the following DID regression:

$$Risk_{it} = \alpha_0 + \alpha_1 Fintech_{it} + \sum_{1}^{k} Control_{i,t} + Macroecnomics_{c,t-1} + YearFE + CountryFE + \epsilon_t$$

[1]

In equation [1], the variable $Risk_{it}$ represents the three measures of risk for bank $i$ in year $t$ (*Non-performance loan ratio, Loan Loss provision* and *impaired loans to equity ratio*), serving as the dependent variable in analysis. A key independent variable in this context is the DID estimator, denoted as $Fintech_{it}$, which signifies the coefficient of interest, denoted as $\alpha_1$ . The vector $Control_{i,t}$ includes various bank-specific determinants of bank risk based on prior research, encompassing metrics such as *Ln (total assets), net loans to total assets ratio, cost to income ratio, equity ratio,* and return on assets (*ROA*). Furthermore, the variable $Macroecnomics_{c,t-1}$ accounts for two control variables representing the macroeconomic conditions of the countries in which the banks are situated. To mitigate the influence of outliers, all continuous variables (including the off-balance sheet item ratio and all control variables) are winsorized at the 1% and 99% levels for each year. Additionally, the term $YearFE$ denotes year fixed effects, capturing the impact of global macroeconomic conditions that affect all bank groups to a similar extent. The term $CountryFE$ signifies fixed effects at the country level, accounting for unobserved nation-specific characteristics. Across all regression specifications, I report Eicker-Huber-White standard errors which ensure a comprehensive understanding of the relationships being examined with unbiased standard errors estimates under heteroscedasticity.

The DIDs model is a widely used quasi-experimental approach that assesses the impact of an intervention by comparing changes in outcomes over time between an intervention group and a control group. This study employs a staggered DIDs model due to the phased rollout of Fintech 3.0 across different units over time, rather than simultaneously. Fintech 3.0 serves as the intervention in this model, with a list of banks with Fintech keyword disclosures forming the treated group. The control group comprises banks that never introduce Fintech 3.0 during the sample period or those that have not yet adopted it. To implement this approach, I create a binary variable named $Fintech_{it}$ within the DIDs model. This variable equals one when a bank group $i$ adopts Fintech 3.0 in year $t$, and zero otherwise. This framework enables the assessment of the impact of Fintech 3.0 by comparing changes in average treatment effects between the treated and control groups over time.

The DID model relies on a key assumption to provide valid estimates of the causal effect: the parallel trends assumption (Dehejia, 2005). This assumption states that, in the absence of the treatment, the trends in the outcomes of the treatment group and the control group would have followed a parallel path over time. In other words, both groups would have shown essentially the same trend of change over time in the outcome variable even without the Fintech treatment. This assumption ensures that any observed differences in outcomes after the treatment can be attributed to the treatment itself and not to pre-existing differences between the groups. I will test this assumption later.

The second assumption is that the assignment of group status is assumed to be randomized. However, in this paper, the adoption of Fintech 3.0 usually results from self-selection by banks, not random assignment Furthermore, straightforward adjustments for covariate variables in the DID regression do not always work, although some approaches have been proposed (Abadie, 2005). To address these issues, this chapter uses the propensity score matching (PSM) method developed by Rosenbaum & Rubin (1983).

Propensity score methods are frequently employed in non-experimental studies to mitigate selection bias. The propensity score refers to the likelihood of being exposed to the target program, determined by specific covariates, and is typically computed using logistic regression. These propensity scores serve to "balance" the program and comparison groups concerning their baseline characteristics, enhancing comparability by minimizing disparities in observed attributes. The PSM method offers several advantages (Stuart et al., 2014). First, it reduces the need for extensive extrapolation and dependence on outcome model specification (Ho, Imai, King, & Stuart, 2007), , enhancing inference robustness. Second, propensity scores condense a set of covariates into a single scalar summary, making balancing techniques more practical. Last, the propensity score methodology operates independently of the outcome variable, separating the study's "design" from its "analysis," reducing potential bias (Rosenbaum, Rosenbaum, & Briskman, 2010; Rubin, 2007).

Common ways of using the propensity score to balance the groups include matching, weighting, and sub-classification (Stuart, 2010). In this study, I use the weighting method. Propensity score weighting assigns each unit different weights to make the treatment and control groups more similar and therefore more comparable. One advantage of using propensity score weighting is its ability to include as much data as possible, which is especially important given the sample sizes in this dataset. Specifically, the kernel matching method is employed, using control variables such as the natural log of total assets and the loan-to-assets ratio as covariates for matching. Figure 3.1 shows the percentage bias for each covariate before and after the matching process. All standardized biases are less than 10%, indicating that systematic differences between the treatment and control groups are eliminated.

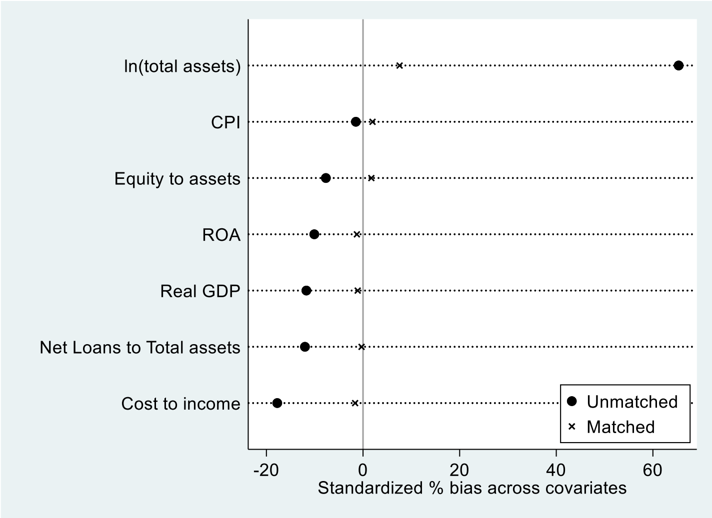



Figure 3.1: Standardized bias

Note: This figure shows the standardized percentage bias across covariates after matching.

After removing unmatched samples, I conduct the examination using the staggered DID model. Table 3.2 presents the test results for equation [1]. The dependent variables are risk measures: the non-performing loan ratio in Panel A, *impaired loans to equity ratio* in Panel B, and *loan loss provision ratio* in Panel C. In each panel, I present the results of two regressions. Generally, there is clear evidence to suggest that, on average, after a bank accesses Fintech, its risk level decreases. Columns (1) and (2) in Panel A show the relationship between *Fintech* and *non-performing loan ratio*, both without and with control variables. In both columns, the coefficients of the DID estimator $Fintech_{it}$ are negative and statistically significant. This indicates that banks with Fintech experience a relatively low *non-performing loan ratio*, with a reduction of 0.35 (0.38 without controls). Similarly, the coefficients of the DID estimator $Fintech_{it}$ are negative and statistically significant in both Panels B and C. Specifically, Panel B indicates a reduction of 2.72 (3.10 without controls) in *impaired loans to equity ratio* for banks with Fintech. Panel C shows that Fintech is associated with a decrease of 2.98 (2.4 without controls) in *loan loss provision ratio*. Overall, these results are consistent with Hypothesis 1a and align with existing studies (e.g., Wang et al., 2023a).

**Table 3.2 (Panel A):** The effect of Fintech on non-performing loan ratio

| Variables | (1)<br>$Non-$<br>$performing\ Loan\ ratio_{i,t}$ | (2)<br>$Non-$<br>$performing\ Loan\ ratio_{i,t}$ |
|---|---|---|
| $Fintech_{i,t}$ | -0.377* | -0.347* |
| | (-1.80) | (-1.95) |
| $\ln(total\ assets)_{i,t}$ | | 0.185*** |
| | | (3.61) |
| $Net\ loans\ to\ total\ asset_{i,t}$ | | -0.010 |
| | | (-1.56) |
| $Cost\ to\ income_{i,t}$ | | 0.009 |
| | | (1.15) |
| $Equity\ to\ assets_{i,t}$ | | 0.221*** |
| | | (4.04) |
| $ROA_{i,t}$ | | -1.003*** |
| | | (-7.13) |
| $GDP_{i,t}$ | | -0.120*** |
| | | (-3.12) |
| $CPI_{i,t}$ | | 0.094*** |
| | | (3.88) |
| *Constant* | 3.470*** | -0.938 |
| | (29.89) | (-0.57) |
| *Country FE* | YES | YES |
| *Year FE* | YES | YES |
| *Observations* | 2,799 | 2,645 |
| *R-squared* | 0.477 | 0.574 |

Note: This panel presents estimates from a baseline regression model [1] examining the relationship between banks' Fintech and bank risk. The dependent variable is bank risk, measured by *non-performing loan ratio*. The treatment variable is Fintech, measured by a dummy variable which equals to one after Fintech introduced and zero otherwise. Column 2 includes *Year* and *Country* fixed effects, along with control variables such as *ln(total assets), Net loans to total asset, Cost to income, Equity to assets, ROA, Consumer Price Index (CPI),* and *GDP per Capita*. Column 1 omits the control variables.

**Table 3.2 (Panel B):** The effect of Fintech on Impaired loans to equity ratio

| Variables | (1)<br>$Impaired\ loans$<br>$to\ equity\ ratio\ _{i,t}$ | (2)<br>$Impaired\ loans$<br>$to\ equity\ ratio\ _{i,t}$ |
|---|---|---|
| $Fintech_{i,t}$ | -3.014** | -2.721** |
| | (-2.12) | (-2.16) |
| $\ln(total\ assets)_{i,t}$ | | 1.321*** |
| | | (3.76) |
| $Net\ loans\ to\ total\ asset_{i,t}$ | | 0.258*** |
| | | (5.61) |
| $Cost\ to\ income_{i,t}$ | | 0.062 |

| | | |
|---|---|---|
| | | (1.07) |
| $Equity\ to\ assets_{i,t}$ | | -0.254 |
| | | (-0.95) |
| $ROA_{i,t}$ | | -5.462*** |
| | | (-4.00) |
| $GDP_{i,t}$ | | -0.507* |
| | | (-1.66) |
| $CPI_{i,t}$ | | -0.058 |
| | | (-0.71) |
| *Constant* | 24.016*** | -9.567 |
| | (30.05) | (-0.87) |
| *Country FE* | YES | YES |
| *Year FE* | YES | YES |
| *Observations* | 2,799 | 2,645 |
| *R-squared* | 0.452 | 0.539 |

Note: This panel presents estimates from a baseline regression model [1] examining the relationship between banks' Fintech and bank risk. The dependent variable is bank risk, measured by *Impaired loans to equity ratio*. The treatment variable is *Fintech*, measured by a dummy variable which equals to one after Fintech introduced and zero otherwise. Column 2 includes *Year* and *Country* fixed effects, along with control variables such as *ln(total assets), Net loans to total asset, Cost to income, Equity to assets, ROA, Consumer Price Index (CPI),* and *GDP per Capita.* Column 1 omits the control variables.

**Table 3.2 (Panel C):** The effect of Fintech on Loan loss provision ratio

| Variables | (1) $Loan\ loss\ provision\ ratio_{i,t}$ | (2) $Loan\ loss\ provision\ ratio_{i,t}$ |
|---|---|---|
| $Fintech_{i,t}$ | -2.454* | -2.979** |
| | (-1.69) | (-2.27) |
| $\ln(total\ assets)_{i,t}$ | | 1.971*** |
| | | (5.64) |
| $Net\ loans\ to\ total\ asset_{i,t}$ | | 0.103** |
| | | (2.49) |
| $Cost\ to\ income_{i,t}$ | | -0.157*** |
| | | (-2.61) |
| $Equity\ to\ assets_{i,t}$ | | 0.810** |
| | | (2.06) |
| $ROA_{i,t}$ | | -6.908*** |
| | | (-4.32) |
| $GDP_{i,t}$ | | -1.074*** |
| | | (-4.61) |
| $CPI_{i,t}$ | | -0.254** |
| | | (-2.02) |
| *Constant* | 21.491*** | -9.734 |
| | (27.79) | (-0.85) |
| *Country FE* | YES | YES |
| *Year FE* | YES | YES |

| | | |
|---|---|---|
| *Observations* | 2,803 | 2,635 |
| *R-squared* | 0.286 | 0.405 |

Note: This panel presents estimates from a baseline regression model [1] examining the relationship between banks' Fintech and bank risk. The dependent variable is bank risk, measured by *Loan loss provision ratio*. The treatment variable is Fintech, measured by a dummy variable which equals to one after Fintech introduced and zero otherwise. Column 2 includes Year and Country fixed effects, along with control variables such as ln(total assets), *Net loans to total asset, Cost to income, Equity to assets, ROA, Consumer Price Index (CPI),* and *GDP per Capita.* Column 1 omits the control variables. I use Eicker-Huber-White standard errors, reported in parentheses beneath coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

**Test of parallel trend assumption**

As mentioned earlier, the parallel trends assumption posits that if there were no treatment, the treatment and control groups would have followed the same trend in the outcome variable both before and after the treatment period. This can be expressed with the following equation:

$$\mathrm{E}[Y^0(1)|\mathrm{E} = 1] - \mathrm{E}[Y^0(0)|\mathrm{E} = 1] = \mathrm{E}[Y^0(1)|\mathrm{E} = 0] - \mathrm{E}[Y^0(0)|\mathrm{E} = 0] \quad [2]$$

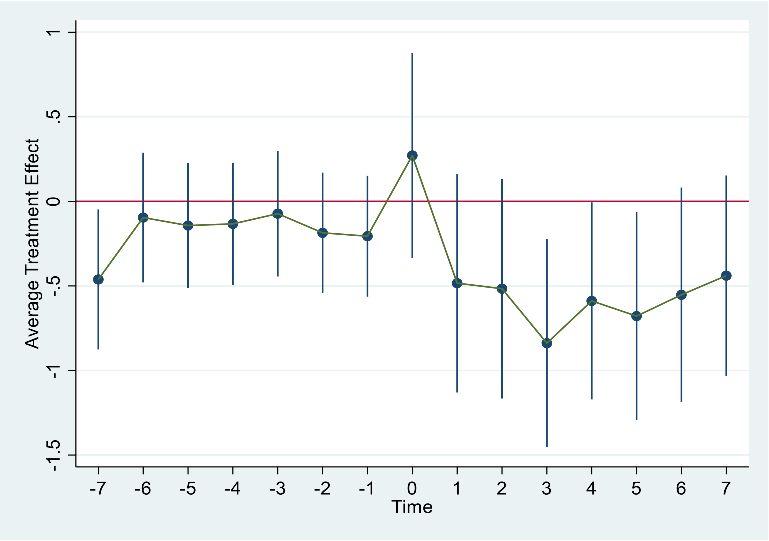
Where $Y^0(1)$ is the after-treatment outcomes for individuals, and Y0(0)$Y$0(0) is the pre-treatment value of outcomes. $\mathrm{E}[1]$ represents the mean of the potential outcome for units in the treatment group, while $\mathrm{E}[0]$ is the mean of the potential outcome for units in the control group. The left side of the equation represents the difference in potential outcomes between the after-treatment period and the pre-treatment period in the treatment group. On the right side of the equation, there is a trend in the potential outcomes under control for the control group units.

In [2], $\mathrm{E}[Y^0(0)|\mathrm{E} = 1]$, $\mathrm{E}[Y^0(0)|\mathrm{E} = 1]$ and $\mathrm{E}[Y^0(0)|\mathrm{E} = 0]$ are all observable. However, $\mathrm{E}[Y^0(1)|\mathrm{E} = 1]$ is unobservable as it represents a counterfactual circumstance where units in the treatment group are not treated in the after-treatment period, making the parallel trends assumption not directly testable. However, in practice, this can be tested through two steps. First, it is essential to establish that there are no differences between the treatment and control groups concerning their pre-treatment outcome variables, known as a "pre-trends test" (Roth, 2022). Second, it is important to show that the impact of the treatment affects both the treatment and control groups equally, allowing us to estimate the divergence in potential outcomes between the groups post-treatment. This is termed the "common shock assumption" (Dimick & Ryan, 2014). Although there is no statistical test for this assumption, I conduct a visual inspection by plotting estimates of the key coefficient over multiple time points.

Following this approach, I test the parallel trends assumption and present the results in Figure 3.2, Panels A, B, and C. Prior to accessing Fintech, there are few significant differences in the non-performing loan ratio, the impaired loans to equity ratio, and the loan loss provision ratio between the two groups (the regression coefficient $\alpha$ pre-treatment is not significantly different from 0), satisfying the parallel trends assumption. However, after Fintech, the three risk measures of the treatment group significantly decrease compared to the control group (the regression coefficient α$\alpha$ post-treatment is significantly greater than 0 at the 1% significance level). This indicates a sustained reduction effect of Fintech access on bank risk.

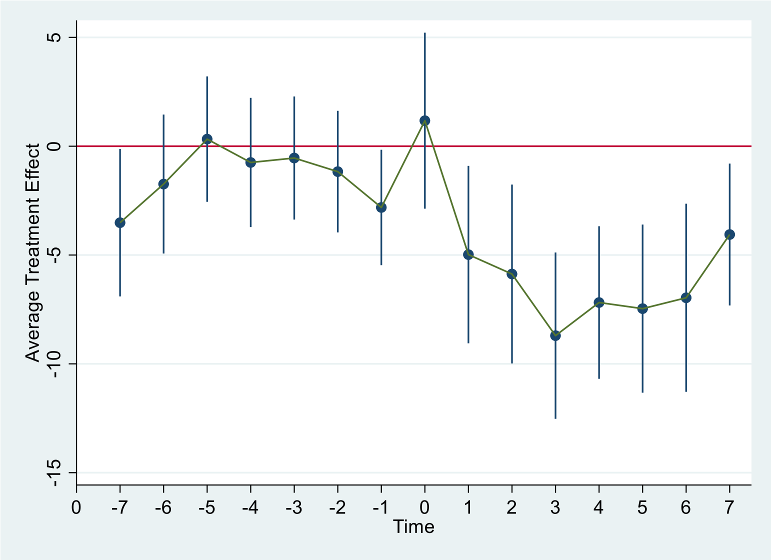
Figure 3.2: Parallel trends assumption test

Panel A: Non-performing loan ratio



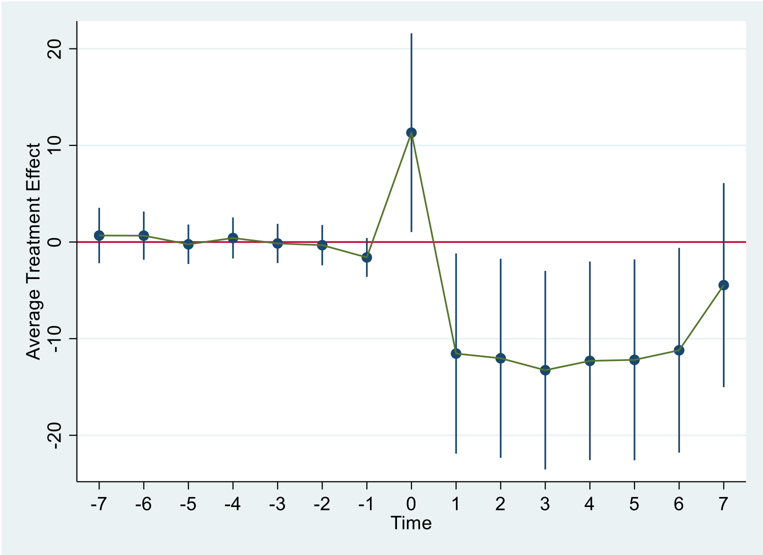

Note: This figure reports a multi-period DID parallel trend test, using a 95% confidence interval where the dependent variable is non-performing loan ratio.

Panel B: Impaired loans to equity ratio




Note: This figure reports a multi-period DID parallel trend test, using a 95% confidence interval where the dependent variable is impaired loans to equity ratio.

Panel C: Loan loss provision ratio




Note: This figure reports a multi-period DID parallel trend test, using a 95% confidence interval where the dependent variable is loan loss provision ratio.

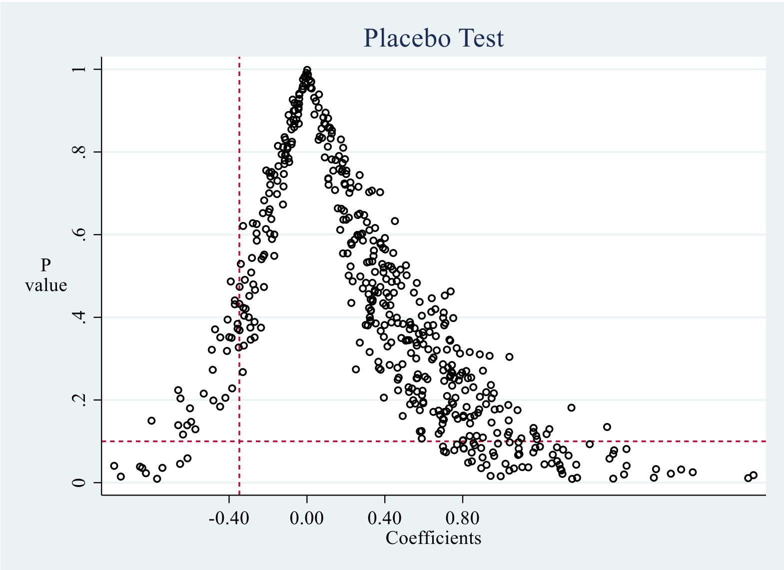
**<u>Placebo test:</u>**

To confirm that the influence of Fintech on bank risk is not driven by unrelated random factors, this study employs a placebo test to assess the coincidental nature of the Fintech effect. Following the methodology of Ferrara, Chong, & Duryea (2012), a procedure is implemented where 500 "pseudo-policy dummy variables" are randomly generated based on the distribution of the Fintech dummy variable used in the previous regression. These pseudo-policy variables are then subjected to regression analysis using equation [1] to assess their coefficient and p-value distributions, visualized in Figure 3.3, Panels A, B, and C. The average regression coefficients for the non-performing loan ratio, the impaired loans to equity ratio, and the loan loss provision ratio, in relation to the "pseudo-policy dummy variables," closely approximate 0 and are significantly smaller compared to those in the baseline regression. The distribution of estimated coefficients resembles a normal distribution, with most p-values exceeding 0.10, thereby not attaining significance at the 10% level. These outcomes indicate that the effects of

Fintech on the non-performing loan ratio, the impaired loans to equity ratio, and the loan loss provision ratio are not triggered by unrelated random factors, thus reinforcing the credibility of the previously drawn conclusions.

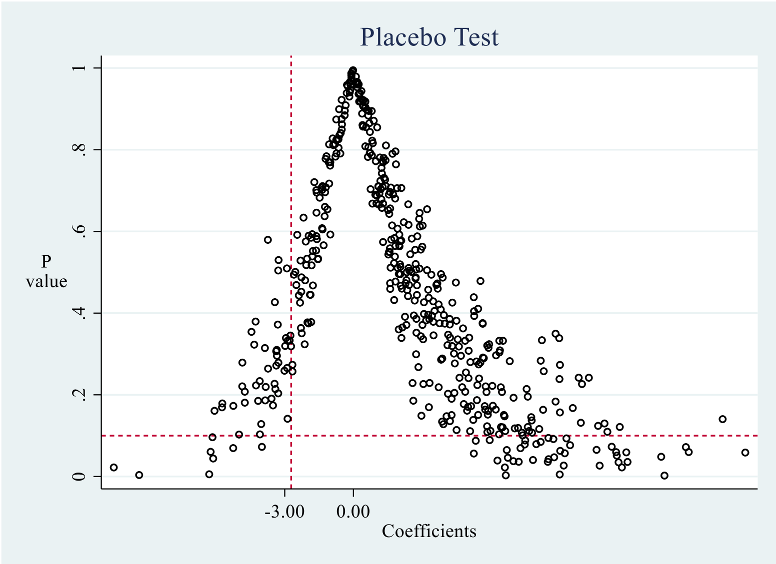
Figure 3.3: Placebo test

Panel A: Non-performing loan ratio



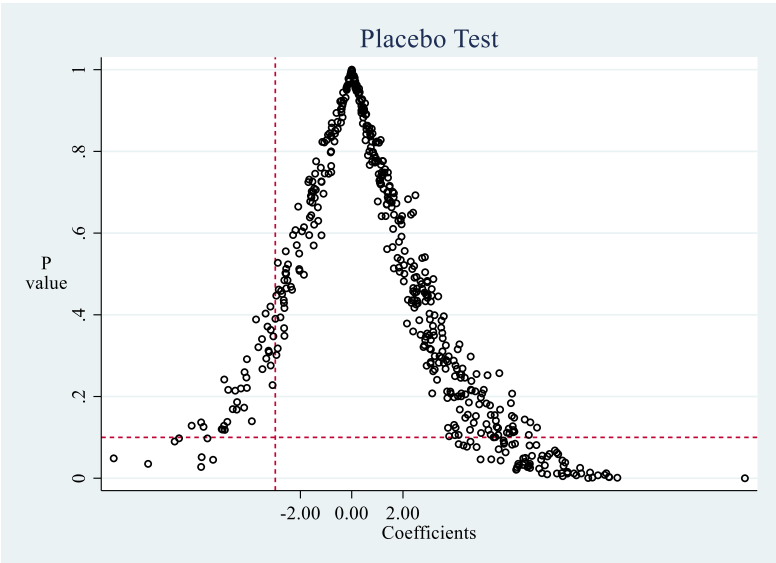

Note: This figure reports the distribution of 500 simulated results of the placebo test, where the dependent variable is non-performance loan ratio, and the treatment indicators were randomly reshuffled.

Panel B: Impaired loans to equity




Note: This figure reports the distribution of 500 simulated results of the placebo test, where the dependent variable is impaired loans to equity, and the treatment indicators were randomly reshuffled.

Panel C: Loan loss provision ratio




Note: This figure reports the distribution of 500 simulated results of the placebo test, where the dependent variable is loan loss provision ratio, and the treatment indicators were randomly reshuffled.

### 3.5.2. The relationship between Fintech and banks' shadow activities

In this section, I present the test result of Hypothesis 2: the identification of the effect of Fintech on banks' shadow activities.

$$BS_{it} = \beta_0 + \beta_1 Fintech_{it} + \sum_{1}^{k} Control_{i,t} + Macroecnomics_{c,t-1} + YearFE + CountryFE + \epsilon_t$$

[3]

In this context, $BS_{it}$, measured by banks' shadow activities (OBS) is the variable serving as the dependent variable. A key independent variable in this context is the DID estimator, denoted as $Fintech_{it}$, which signifies the coefficient of interest, denoted as $\beta_1$. The vector $Control_{i,t}$ encompasses various bank-specific determinants of bank risk, drawing from existing literature. These determinants include *Ln (total assets)*, *net loans to total assets ratio, cost to income ratio, equity ratio,* and return on assets (*ROA*). The variable $Macroecnomics_{c,t-1}$ signifies two control variables evaluating the macroeconomic conditions of the respective countries where the banks are situated.

To ensure the robustness of the analysis, all continuous variables (off balance sheet item ratio and all control variables) were subjected to winsorization at the 1% and 99% levels for each year, thereby addressing the presence of outliers. Moreover, the term $Year$ pertains to year fixed effects that account for the global macroeconomic conditions influencing all bank groups uniformly. On the other hand, $Country$ signifies the fixed effects at the country level, capturing latent nation-specific characteristics. In this regression specifications, I employ Eicker-Huber-White standard error assuming that the estimated standard errors for the coefficients are adjusted to account for potential heteroscedasticity and potential correlation of errors within clusters.

**Table 3.3**: The effect of Fintech on banks' shadow activities

| Variables | (1)<br>$OBS_{i,t}$ | (2)<br>$OBS_{i,t}$ |
|---|---|---|
| $Fintech_{i,t}$ | 0.029*** | 0.004 |
| | (4.54) | (0.70) |
| $\ln(total\ assets)_{i,t}$ | | 0.038*** |
| | | (23.53) |
| $Net\ loans\ to\ total\ asset_{i,t}$ | | 0.002*** |
| | | (10.74) |
| $Cost\ to\ income_{i,t}$ | | 0.001*** |
| | | (3.66) |
| $Equity\ to\ assets_{i,t}$ | | -0.001** |
| | | (-2.02) |
| $ROA_{i,t}$ | | 0.004*** |
| | | (2.74) |
| $GDP_{i,t}$ | | 0.002** |
| | | (1.97) |
| $CPI_{i,t}$ | | 0.001** |
| | | (2.19) |
| *Constant* | 0.202*** | -0.601*** |
| | (88.76) | (-15.65) |
| *Country FE* | YES | YES |
| *Year FE* | YES | YES |
| *Observations* | 4,565 | 4,462 |
| *R-squared* | 0.306 | 0.414 |

Note: This table presents estimates from the regression model [3] examining the relationship between banks' Fintech and banks' shadow activities. The dependent variable is banks' shadow activities, measured by off-balance sheet item ratio. The treatment variable is Fintech, measured by a dummy variable which equals to one after Fintech introduced and zero otherwise. Column 2 includes Year and Country fixed effects, along with control variables such as *ln(total assets), Net loans to total asset, Cost to income, Equity to assets, ROA, Consumer Price Index (CPI),* and *GDP per Capita*. Column 1 omits the control variables. I use Eicker-Huber-White standard errors, reported in parentheses beneath coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Table 3.3 summarizes the results of the test, showing the effects of Fintech on banks' shadow activities (OBS) across two models: without control variables (Column 1) and with control variables (Column 2). The positive coefficient of the DID estimator suggests that, on average, the introduction of Fintech tends to lead to a higher level of banks' shadow activities. However, the lack of statistical significance implies that the observed positive effect could be due to chance or noise in the data.

There are two possible interpretations of these findings. First, Fintech may not significantly increase banks' participation in shadow activities. This is because Fintech enhances financial transparency by providing more accessible, real-time data collection, processing, analysis, and presentation to stakeholders. Such innovations lead to more accurate and timely reporting of financial and operational metrics, potentially offsetting shadow activities to some extent (Omarova, 2020; Rerung, Paranita, AY, Budiandru, & Tandililing, 2024). The second interpretation suggests that Fintech 3.0 might indeed increase banks' involvement in shadow banking activities, but these activities are conducted more discreetly. For example, banks may collaborate with unregulated third parties to create innovative financial products and services, exploiting gaps in the current regulatory framework (Barakova, Ehrentraud, & Leposke, 2024; Wiktor & Wadeusz, 2025).

Additionally, the impact of Fintech on banks' shadow activities depends on the bank's operating model. For banks focused on traditional lending, the impact is less pronounced due to their conservative nature, leading them to proceed cautiously with off-balance sheet operations. In contrast, banks more active in non-traditional investing find Fintech to be a catalyst for increased engagement in shadow banking. Fintech provides these banks with advanced tools to overcome historical limitations and explore areas like proprietary trading, aligning with their expertise. Such activities may include creating new financial instruments or off-balance sheet operations, allowing these banks to capitalize on the flexibility and innovation Fintech offers (Chiorazzo, D'Apice, DeYoung, & Morelli, 2018; Krahnen, Noth, & Schüwer, 2017; Lv & Xiong, 2022).

To test this conjecture, I estimate equation [3] for two subsamples of banks: those engaging in a wider range of activities, especially investment activities (High), and those focusing on more traditional lending activities (Low). The subsamples are divided based on the *NIS/NIM* ratio. Traditional banks that primarily focus on deposit and lending activities typically have a total value of interest-earning assets greater than interest-bearing liabilities, resulting in a lower *NIS/NIM* ratio. Conversely, banks engaging in a wider range of activities, particularly investment, may not generate significant interest income, leading to a higher *NIS/NIM* ratio.

**Table 3.4**: The effect of Fintech on banks' shadow activities (Sub-samples)

| Variables | $OBS_{i,t}$ (1) Full sample | (2) Low-NIS/NIM ratio | (3) High-NIS/NIM ratio |
|---|---|---|---|
| $Fintech_{i,t}$ | 0.007 | 0.002 | 0.029** |
| | (1.22) | (0.27) | (2.57) |
| $\ln(total\ assets)_{i,t}$ | 0.036*** | 0.042*** | 0.035*** |
| | (21.42) | (17.93) | (10.92) |
| $Net\ loans\ to\ total\ asset_{i,t}$ | 0.002*** | 0.002*** | 0.001*** |
| | (11.00) | (7.44) | (4.70) |
| $Cost\ to\ income_{i,t}$ | 0.001*** | 0.001*** | -0.000 |
| | (3.79) | (4.11) | (-0.28) |
| $Equity\ to\ assets_{i,t}$ | -0.002** | -0.002* | -0.003*** |
| | (-2.40) | (-1.85) | (-2.89) |
| $ROA_{i,t}$ | 0.005*** | 0.007** | 0.000 |
| | (2.67) | (2.24) | (0.22) |
| $GDP_{i,t}$ | 0.001 | 0.001 | 0.001 |
| | (1.33) | (1.08) | (0.28) |
| $CPI_{i,t}$ | 0.000* | 0.000 | 0.001 |
| | (1.71) | (1.26) | (0.26) |
| *Constant* | -0.571*** | -0.668*** | -0.501*** |
| | (-14.28) | (-14.10) | (-6.58) |
| *Company FE* | YES | YES | YES |
| *Year FE* | YES | YES | YES |
| *Observations* | 4,250 | 3,189 | 1,058 |
| *R-squared* | 0.426 | 0.460 | 0.583 |

Note: This table presents estimates from the equation [3] examining the relationship between banks' Fintech and banks' shadow activities in sub-samples. The dependent variable is banks' shadow activities, measured by *off-balance sheet item ratio*. The treatment variable is *Fintech*, measured by a dummy variable which equals to one after Fintech introduced and zero otherwise. Column 1 indicates the result of a full sample including *Year* and *Country* fixed effects, along with control variables such as *ln(total assets), Net loans to total asset, Cost to income, Equity* *to assets, ROA, Consumer Price Index (CPI),* and *GDP per Capita*. Column 2 indicates the result of a sub-sample of a lower level of *NIS/NIM* ratio. Column 3 indicates the result of a sub-sample of a higher level of *NIS/NIM* ratio. I use Eicker-Huber-White standard errors, reported in parentheses beneath coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Table 3.4 provides the results from the subsamples. Columns (1), (2), and (3) show the results for banks in the full sample, banks engaging in a wider range of activities, especially investment activities (High), and banks focusing on more traditional lending activities (Low). The results reveal interesting dynamics among banks with more investing activities after the adoption of Fintech. Following the treatment, the coefficient of the DID estimator ($\beta_1$) for banks that rely more heavily on investing activities is positive and statistically significant at the 10% confidence level. This suggests that Fintech leads to an increase in the off-balance sheet ratio by approximately 0.029 for this subset of banks (High). However, when focusing on a subsample of traditional lending banks (Low), the coefficient of 0.25 is not statistically significant. This implies that the impact of Fintech on banks' shadow activities is not uniform across different banking profiles, as evidenced by the divergence in results between traditional lending banks and those emphasizing investing. Compared to traditional lending banks, banks that engage in more investing activities increase shadow activities after adopting Fintech.

### 3.5.3. Effect of Fintech on banks' shadow activities and risk

To verify whether the impact of banks' shadow activities on bank risk vary after the staggered introduction of Fintech (Hypothesis 3), I compose the following equation:

$$\begin{aligned} Risk_{it} = \gamma_0 + \gamma_1 Fintech_{it} + \gamma_2 BS_t * Fintech_{it} + \gamma_3 BS_t \\ + \sum_1^k Control_{i,t} + Macroecnomics_{c,t-1} + YearFE \\ + CountryFE + \epsilon_t \end{aligned}$$

[4]

Where $Risk_{it}$ is the matrix of bank risk measures for bank $i$ in year $t$ and it is the dependent variable. The key independent variable here is $BS_{i,t}$ with the coefficient of interest denoted as $\gamma_1$ , capturing the conditional relationship between the risk measure and banks' shadow activities, specifically the off-balance sheet item ratio ($OBS$). The vector $Control_{i,t}$ captures several bank-specific determinants of bank risk based on prior literature, including Ln (total assets), net loans to total assets ratio, cost to income ratio, equity ratio, and return on assets (ROA). $Macroecnomics_{c,t-1}$ represents two control variables that measure the macroeconomic conditions of each country where banks are located. To remove the outliers, I winsorize all continuous variables (off balance sheet item ratio and control variables) at the 1% and 99% levels each year. What is more, $YearFE$ denotes year fixed effects accounting for global macroeconomic conditions affecting all bank groups to the same degree. $CountryFE$ denotes the fixed effects at the country level, capturing latent nation-specific characteristics. In this regression specifications, I employ Eicker-Huber-White standard error assuming that the estimated standard errors for the coefficients are adjusted to account for potential heteroscedasticity and potential correlation of errors within clusters.

**Table 3.5**: The relationship between Fintech, banks' shadow activities and bank risks

| Variables | (1) $Impaired\ loan\ to\ equity\ ratio_{i,t}$ | (2) $Non\ performing\ Loan\ ratio_{i,t}$ | (3) $Loan\ loss\ provision\ ratio_{i,t}$ |
|---|---|---|---|
| $Fintech_{i,t} * OBS_{i,t}$ | 17.991*** | 1.594** | 6.090 |
| | (2.98) | (1.96) | (1.12) |
| $Fintech_{i,t}$ | -6.213*** | -0.397 | -1.523 |
| | (-3.41) | (-1.53) | (-1.04) |
| $OBS_{i,t}$ | -23.745*** | -1.350** | -4.074 |
| | (-6.11) | (-2.12) | (-1.25) |
| $\ln(total\ assets)_{i,t}$ | 2.675*** | 0.217*** | 1.468*** |
| | (8.52) | (4.91) | (5.05) |
| $Net\ loans\ to\ total\ asset_{i,t}$ | 0.238*** | -0.017*** | 0.037 |
| | (6.60) | (-3.04) | (1.28) |
| $Cost\ to\ income_{i,t}$ | 0.268*** | 0.026*** | -0.132** |

| | | | |
|---|---|---|---|
| | (5.19) | (3.90) | (-2.23) |
| $Equity\ to\ assets_{i,t}$ | -0.126 | 0.167*** | 0.635*** |
| | (-0.71) | (4.43) | (3.18) |
| $ROA_{i,t}$ | -4.373*** | -0.768*** | -8.797*** |
| | (-4.20) | (-6.64) | (-6.69) |
| $GDP_{i,t}$ | -0.207 | -0.064* | -1.461*** |
| | (-0.74) | (-1.96) | (-8.52) |
| $CPI_{i,t}$ | 0.034 | 0.098*** | -0.399** |
| | (0.38) | (3.63) | (-2.37) |
| *Constant* | -40.747*** | -1.426 | 7.972 |
| | (-4.77) | (-1.21) | (1.09) |
| *Country FE* | YES | YES | YES |
| *Year FE* | YES | YES | YES |
| *Observations* | 4,387 | 4,387 | 4,411 |
| *R-squared* | 0.564 | 0.594 | 0.441 |

Note: This table presents estimates from the equation [4] examining the relationship between banks' Fintech, banks' shadow activities and bank risks. The dependent variable is bank risk, measured by *Impaired loans to equity ratio* (Column 1), *Non-performing Loan ratio* (Column 2) and *Loan loss provision ratio* (Column 3). The treatment variable is Fintech, measured by a dummy variable which equals to one after Fintech introduced and zero otherwise. *Year* and *Country* fixed effects are controlled, along with control variables such as *ln(total assets), Net loans to total asset, Cost to income, Equity to assets, ROA, Consumer Price Index (CPI),* and *GDP per Capita*. I use Eicker-Huber-White standard errors, reported in parentheses beneath coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% levels.

Following this thread, Table 3.5 presents the estimation of equation 4. The coefficient of interest, $\gamma_2$, represents the coefficient of interaction between $Fintech_{it}$ and $BS_t$. It estimates whether the documented negative relationship between banks' shadow activities and bank risk varies before and after the implementation of Fintech 3.0. As shown in column (1) of Table 3.5, where the dependent variable is *impaired loans to equity ratio,* $\gamma_2$ is indeed positive and statistically significant. This result, together with the conclusion drawn in Chapter 2, which establishes a negative relationship between banks' shadow activities and bank risk, reveals two crucial findings. First, for both banks with Fintech (the treatment group) and banks without Fintech (the control group), as the level of banks' shadow activities increases, bank risk tends to decrease. Second, the positive coefficient associated with the interaction term indicates that the introduction of Fintech has weakened the decline in bank risk for the treatment group compared to the control group. Essentially, the influence of banks' shadow activities on reducing bank risk has diminished during the post-Fintech period. Furthermore, the estimations in columns (2) and (3) of Table 3.5, which replace the dependent variables with the non-performing loan ratio and the loan loss provision ratio, respectively, demonstrate similar results. The coefficient $\gamma_2$ remains positive and statistically significant for the non-performing loan ratio, aligning with the aforementioned outcome. However, when the dependent variable shifts to *loan loss provision ratio*, $\gamma_2$ retains a positive sign but loses some statistical significance. These results are consistent with the hypotheses, confirming the findings.

## 3.6. Conclusion

The examination of the recent Fintech integration within banking underscores its significant impact on bank risk management and banks' shadow activities. To explore the relationship between Fintech, bank risk and shadow banking, I employ Difference-in-Differences (DID) models along with statistical methods such as Propensity Score Matching (PSM), parallel trend tests, and placebo tests.

The findings show that banks adopting Fintech innovations generally experience a reduction in realized risk levels. This aligns with existing literature and highlights Fintech's positive role in enhancing risk assessment and operational efficiency. However, the influence of Fintech on banks' engagement in shadow banking activities is not significant on average. While Fintech adoption broadly involves changes in these activities, it is particularly significant among banks with substantial investment operations. These banks tend to increase their shadow activities following Fintech integration, suggesting that technology enables more aggressive strategies within off-balance-sheet operations.

Also, the research reveals that while Fintech adoption is associated with a decrease in risk across traditional metrics, it paradoxically challenges banks' risk management capabilities concerning shadow activities. In this sense, banks' shadow activities can diminish the beneficial inverse relationship between Fintech adoption and bank risk.

Furthermore, the study identifies the limitations of internal capital markets and management capabilities in mitigating the risks posed by bank complexity. These mechanisms, although integral to conventional risk management, fall short in addressing the complexities introduced by concurrent Fintech adoption and shadow banking engagement.

One of the key limitations of this study is the issue of endogeneity arising from the self-selected nature of Fintech adoption by banks. The decision to integrate Fintech is not random and often determined by internal strategic considerations, which may lead to biases in assessing its impact on risk and banks' shadow activities. Addressing this limitation could involve exploring alternative methodological approaches, such as using instrumental variables or randomized controlled trials, to strengthen causal inferences.

Overall, the research highlights the need for financial institutions to reconsider their strategic positioning as they integrate Fintech solutions. It underscores the necessity for comprehensive risk management frameworks that account for the dual influence of technological advancements and evolving shadow banking practices. Policymakers and bank executives must ensure that regulatory and strategic oversight keeps pace with the rapid changes in the financial landscape to maintain stability and capitalize on the benefits of technological progress.

# Chapter 4
# Banks' Fintech Adoption, Information Asymmetries, and Cost of Bank Debt

## 4.1. Introduction

Prior studies have explored the relationships between a firm's cost of debt and factors such as corporate governance, firm age, government relations, competition, and economic and regulatory conditions (e.g. Cassar, Ittner, & Cavalluzzo, 2015; Sakai, Uesugi, & Watanabe, 2010). However, very few studies specifically examine the extent to which banks' financial technology (Fintech) adoption may affect firms' cost of debt. The objective of this chapter is to fill this gap by providing empirical evidence on the effects of banks' Fintech adoption on firms' cost of debt and the underlying economic mechanisms.

Due to limited data availability and the lack of direct proxies for measuring the level of Fintech adoption within banks (the lenders), research on banks' Fintech adoption and its impact on firms (the borrowers) is restricted. This study seeks to develop a unique and more direct measure—the Firm-Bank Fintech Influence Score (FBFTIS)—to examine the impact of lending banks' Fintech adoption on corporate clients' borrowing costs. Specifically, I construct a bank-level Fintech index using text analysis techniques and allocate it to firms based on a loan-weighted distribution method.

Fintech has transformed financial services, with Fintech startups and big-tech firms reshaping financing activities and client behaviors. Current research on Fintech places significant emphasis on peer-to-peer (P2P) lending platforms operated by Fintech companies, emerging technological innovations such as artificial intelligence (AI) algorithms, blockchain, big data, and cloud computing technologies, and novel financial instruments like cryptocurrencies (Allen, Gu, & Jagtiani, 2020; Oyewole &

Adegbite, 2023). However, these studies tend to overlook the reactions of traditional financial institutions, such as banks, to the Fintech transformation (Thakor, 2020). Given the current vital and central role of banks in the financial market, debt remains the dominant source of external financing, crucial for firms' operating flexibility and the funding of real investment activities. Thus, it is important to understand whether and how Fintech transformation affects non-bank entities receiving financial services from banks.

Specifically, I propose two opposing hypotheses to reflect both sides of the argument. On the one hand, I argue that banks' Fintech adoption may lower the cost of bank debt for borrowing firms if it reduces the information asymmetries between borrowers and lenders. Specifically, the reduction in information asymmetry lowers the costs associated with pre-lending screening and post-loan monitoring. It also reduces the need for banks to charge premiums to compensate for unobservable risks, resulting in a lower cost of debt. On the other hand, banks' Fintech adoption may increase the cost of bank debt for borrowing firms. When banks invest in Fintech, they often incur substantial upfront costs, including capital expenditure and training expenses, which may take several years to recover. To safeguard their financial health from the potential negative impacts of these investments, banks might adopt strategies to offset these costs. One such strategy could be to increase revenue through the interest generated from loans, leading to a higher cost of debt for borrowing firms.

The findings show a significantly negative relationship between banks' Fintech adoption and firms' cost of bank debt. One mechanism explaining this effect is the reduced information asymmetry between lending banks and borrowing firms. Specifically, borrowing firms facing information gaps or financial constraints may benefit from lower bank debt costs, as higher Fintech adoption by their lending banks reduces adverse selection. Additionally, a reduction in moral hazard offers a plausible explanation. Borrowing firms with a lower risk-taking tendency and greater management efficiency after receiving loans tend to experience lower bank debt costs when their lenders have higher Fintech adoption. In additional analysis, I find insufficient evidence to suggest that the cost of bank debt reduction is more significant for firms with fewer fixed assets. Furthermore, the decrease in operational costs of lending banks does not explain the reduction in the cost of borrowing due to banks' Fintech adoption. One concern in this study is that the results may be affected by endogeneity because banks with more advanced Fintech development might favor firms with lower risk, leading to a lower cost of debt. To address this concern, I applied a two-stage least squares regression (2SLS) and a Difference-in-Differences (DID) approach. The findings remain robust.

This study makes contributions to the literature in three ways. First, it provides evidence that banks' Fintech adoption contributes to reducing borrowing firms' cost of bank debt. Existing research has shown that the development of Fintech enhances the efficiency of capital allocation and information transmission, thereby improving loan supply, access, and capital growth (Dong & Yu, 2023; Erel & Liebersohn, 2022; Kutzbach & Pogach, 2024; Wu et al., 2024). This paper extends this stream of literature by examining the specific impact of Fintech adoption on the cost of bank debt, offering new insights into how banks can support the real economy through technological advancements. Empirical evidence has demonstrated that Fintech adoption enhances bank performance, mitigates bank risk, and facilitates the transformation of business practices, enabling banks to gain market share (Bian, Wang, & Xie, 2023; Gopal & Schnabl, 2022; Kutzbach & Pogach, 2024). However, these studies mainly examine the impact of Fintech on firms from a spatial perspective (Chen, Wu, & Zhang, 2023; Ding, Gu, & Peng, 2022). Therefore, this paper contributes to the literature by employing a more direct measure of the impact of Fintech adoption on firms, thereby highlighting the broader implications beyond spatial constraints.

Second, the paper contributes to the literature on information asymmetry and firms' borrowing costs. Relationship banking is commonly regarded as a mechanism for bridging the information gap between banks and borrowers, thereby reducing information asymmetry (Berger & Udell, 1995). The reduction of information asymmetry can be achieved through other mechanisms, such as the use of financial intermediaries in producing and processing information (Diamond, 1984), the use of credit scoring models to standardize credit assessments (Avery, Bostic, & Samolyk, 1998), and the impact of technological advancements on enhancing data collection and analysis (Philippon, 2016). However, the debate on how information asymmetry can be resolved via Fintech remains limited. This study adds new evidence on the specific conditions and mechanisms through which the reduction of information asymmetry via Fintech adoption leads to decreased borrowing costs. By examining various drivers of information asymmetry, this study offers additional insights into how Fintech adoption by banks can effectively mitigate information asymmetry, resulting in tangible benefits for both debtholders and borrowers.

Third, this paper contributes to the literature by elucidating the information perspectives leveraged through Fintech adoption as a channel to reduce borrowing costs. While existing research highlights the role of data analytics, alternative data sources, and machine learning in improving credit assessments (Berg, Burg, Gombović, & Puri, 2020; Fuster, Plosser, Schnabl, & Vickery, 2019), this study advances the understanding of how Fintech adoption enhances banks' judgement in credit allocation accuracy, thereby optimizing the distribution strategy of credit. By focusing on the perspectives that enable banks to better predict future firm performance, this paper sheds light on the channels through which Fintech adoption effectively reduces the cost of bank debt.

The remaining sections of the paper are organized as follows. Section 2 describes the background and literature on Fintech adoption in the banking industry. In Section 3, I develop the hypotheses. I explain the research design and describe the sample and data in Sections 4. The empirical results are described in Sections 5 and 6 and 7 concludes.

## 4.2. The development and impact of Fintech in China

### 4.2.1. The development of Fintech in China

China's Fintech sector has developed rapidly, driving the digital transformation of finance in the country over the years. According to the People's Bank of China (PBOC), China's Fintech investment surged to $25.5 billion in 2018, marking a 900% increase from the previous year and representing more than half of the global total. By 2023, China's Fintech market had grown to an estimated $42.8 billion, reflecting a continued strong growth trajectory. This rapid development is further evidenced by the increasing adoption of digital payment systems, with mobile payment transactions in China reaching 432 billion in 2022, up from 257 billion in 2018 (China Digital Finance Survey Report, 2022). The rapid growth of China's Fintech industry is also reflected in the significant global impact and leadership of Chinese Fintech companies. For instance, on the list of the top 100 Fintech companies globally in 2017, Ant Financial, which is from the Chinese Alibaba Group, has become the largest Fintech company in the world (KPMG, 2017).

### 4.2.2. The impact of Fintech on China's banking industry

The Chinese government has played a pivotal role in this transformation by encouraging the development of bank Fintech. The Financial Technology Development Plan (2022–2025) issued by the PBOC emphasizes the importance of accelerating the digital transformation of financial institutions and constructing a modern financial system that aligns with the development of the digital economy. This policy highlighted the necessity for banks to enhance their quality and efficiency by employing Fintech. In response, banks have increasingly collaborated with Fintech companies to integrate advanced technologies into their operations. For example, the Industrial and Commercial Bank of China (ICBC) has partnered with Ant Financial, the parent company of Alipay, to develop its mobile banking app. This collaboration has integrated Ant Financials' advanced Fintech solutions, such as AI-driven customer service and big data analytics, into ICBC's app, providing users with a more seamless and personalized banking experience.

The flourishing of Fintech has significantly reshaped the banking industry. To grasp the core financial technologies and compete with Fintech companies, commercial banks have also invested in developing their own Fintech capabilities. The 2022 China Digital Finance Survey Report shows that the proportion of users of personal mobile banking has increased from 57% in 2018 to 86% in 2022, indicating a strong adoption of these new services. In terms of Fintech adoption, traditional financial institutions need to build branches to expand services, while high costs make it difficult for them to penetrate relatively impoverished regions. However, Fintech development can overcome such shortcomings. In some areas, customers can access essential financial services through terminal devices such as computers and mobile phones even in the absence of physical infrastructure such as bank branches and ATMs. Wang and Wu (2024) record that firms receive increased bank lending following the introduction of mobile banking apps by their banks, especially when the number of physical branches is reduced. This finding indicates a trend where banks use mobile banking to replace physical branches.

China's financial system is predominantly bank-based, with banks playing a central role in providing affordable financial support to firms. As a result, bank loans remain a more attractive financing option compared to alternative sources. Additionally, China's Fintech sector is growing rapidly relative to developed countries, benefiting from fewer innovation barriers and offering more development space (Goldstein, Jiang, & Karolyi, 2019). The banking industry's unique and essential role in supporting the real economy makes the study of Fintech adoption by Chinese banks and the impact particularly valuable (Allen, Qian, & Qian, 2005).

## 4.3. Literature review and hypothesis development

### 4.3.1. Firms' cost of debt

The cost of debt encompasses the interest and other expenses a firm incurs on borrowed funds, which is a crucial factor in evaluating its financial health. Existing literature suggests that the cost of bank debt for firms is influenced by a variety of firm-specific factors. For instance, firms with higher disclosure quality tend to have lower costs of debt, particularly in times of greater market uncertainty (Merritt, 2013; Sengupta, 1998). Also, financial health metrics such as firm size, cash flow, profitability, liquidity ratios play a significant role in determining the cost of debt (Cassar et al., 2015). In addition, the quality and value of a firm's collateral can reduce lender risk and, consequently, the interest rate charged. Sakai, Uesugi and Watanabe (2010) indicated that larger firms established for more years often benefit from lower borrowing costs due to their perceived stability and lower default risk. Additionally, firms in stable, less competitive industries may enjoy lower borrowing costs compared to those in competitive sectors (Valta, 2012).

At the macro level, economic and market conditions may significantly impact firms' cost of bank debt. For instance, during economic uncertainty or recession, borrowing costs may rise due to increased default risk. In such cases, a loose monetary policy is often introduced, leading to higher interest rates and increased borrowing costs for firms. Conversely, high inflation can also result in higher interest rates as lenders seek to offset the reduced purchasing power of repaid money, typically accompanied by a tight monetary policy that lowers interest rates and borrowing costs for firms. Additionally, regulatory and legal factors, such as capital requirements, reserve requirements, and tax treatments, may also influence borrowing costs (Ashraf, 2021; Ashraf & Shen, 2019; Butler, Cornaggia, & Gurun, 2017; Fraisse, Lé, & Thesmar, 2019; Nguyen, Nguyen, & Ho, 2024; Wu, Yan, Chen, & Jeon, 2022).

### 4.3.2. Borrower-lender information asymmetry and cost of debt

Despite growing interest in Fintech, the influence of banks' Fintech adoption on the cost of debt for borrowing firms remains underexplored in existing literature. This influence is primarily driven by the mitigation of information asymmetry, a common challenge in lending. Information asymmetry can lead to costs of bank debt through two main sub-channels: screening costs incurred to minimize concerns of adverse selection, and risk premium charges to compensate for concerns of moral hazard.

*Concerns about adverse selection arising from hidden or false information give rise to screening cost:* Adverse selection is a situation where lenders, as an outsider of the borrowing firms, have less information on the borrowing firm's probability of defaulting on loans and lead to poor loan decisions (Bharath, Sunder, & Sunder, 2008). As a result, banks often incur substantial screening costs before extending credit to mitigate adverse selection arising from false or hidden information. This process involves evaluating the pre-loan risk level of potential borrowers in loan repayment. This process involves evaluating the pre-loan risk level of potential borrowers by considering various factors such as past financial performance, credit history, and information on management's character (Cassar et al., 2015).

*Concerns about moral hazard arising from post-lending risks leads to additional risk premium charges:* Moral hazard occurs when borrowing firms engage in risky behavior that is not in the best interest of the lender. For instance, a borrowing firm may divert effort away from their loan-funded project to other activities, knowing that the cost of that arbitration (increased probability of loan defeat) is attributed to lending banks, whereas the benefit is fully captured by the firm. Banks charge risk premiums in advance to compensate for after-lending risks arising from moral hazard, such as firms' managerial risk-seeking behaviors. These premiums may also be relevant for firms with long-term debt, which may be perceived as having higher rollover risk (Baldenius, Deng, & Li, 2024; Wang, Chiu, & King, 2020).

### 4.3.3. Fintech adoption, information asymmetry, and cost of debt

Fintech adoption by banks can significantly decrease the cost of bank debt through reducing cost incurred by adverse selection. On the one hand, by automating the screening process, Fintech adoption enhances efficiency, reducing labor expenses and transaction costs for lenders. This allows banks to reduce screening costs embedded in the cost of bank debt (Jiang, Cuesta, Jørring, & Xu, 2023). On the other hand, Fintech adoption reduces adverse selection by enhancing data collection and analysis, thereby further minimizing pre-lending hidden information. It enables banks to gather and analyze a broader range of data, including non-traditional sources like social media, providing a more comprehensive view of borrowers' financial health and creditworthiness (Berg, Burg, Gombović, & Puri, 2019).

Also, Fintech adoption by banks can significantly decrease the cost of bank debt through reducing risk premium incurred by moral hazard. By leveraging big data and advanced AI algorithms, such as deep learning and natural language processing, Fintech enables a more comprehensive and sophisticated evaluation in terms of firms' after-lending risk-taking behaviors, which may have been previously unobservable by banks. As a result, moral hazard risks related to the lending are moderated, lessening the need for banks to attach uncertainty premiums to the cost of bank debt, leading to lower costs of bank debt for borrowing firms (Chen et al., 2023; Wang et al., 2023a).

However, some arguments suggest that Fintech adoption in the banking industry may potentially increase the cost of bank debts. For example, Fintech adoption can eliminate the information advantage of relationship lending. In a traditional lending activity, ongoing banking relationships are regarded as one of the main sources of information to compensate for information asymmetries. The information is made mainly by subjective factors such as a loan officer's personal knowledge, trust and reputation of the potential borrower.  As Herpfer (2021) shows, bankers and their relationships with borrowing firms significantly influence debt prices. However, banks relying on Fintech are more impersonal and prioritize quantitative data over qualitative assessments based on personal relationships when determining loan prices (Das, 2019). Therefore, as the value of ongoing bank relationships is weakened by Fintech adoption, the reduction in information asymmetries achieved through bank relationships diminishes, and firms may face higher interest rates, leading to an increase in their overall cost of bank debt.

Secondly, the cost of Fintech adoption can be transferred to borrowers, therefore increasing the cost of debt for the borrowers. Fintech adoption is costly, and due to the rapid pace of innovation in Fintech, banks are expected to continually increase their investment to remain competitive (Aral & Weill, 2007). These upfront costs create a financial friction, taking several years to recover, which negatively impacts banks' profitability (Citterio, King, & Locatelli, 2024). Consequently, to maximize expected profits, banks may pass through these costs to the borrowing firms. As Kalda & Pearson (2023) and Sovich (2023) suggest, in the US mortgage market, when lenders experience cost shocks, such as increases in funding costs or other financial pressures, they usually transfer these costs to borrowers by adjusting the interest rates on the mortgages. This means that any increase in the lenders' costs could be reflected in higher interest rates for the borrowers, further exacerbating the cost of bank loans.

Overall, the dominant effect of banks' Fintech adoption on the cost of bank debt is still unclear. Therefore, I propose the following testable hypothesis:

*Hypothesis 1a: Firms that borrow from banks with a higher level of Fintech development experience lower cost of bank debts.*

*Hypothesis 1b: Firms that borrow from banks with a higher level of Fintech development experience higher cost of bank debts.*

## 4.4. Variables and data

### 4.4.1. Dependent variable

The primary dependent variable in this analysis is the cost of bank debt. Following Kim, Simunic, Stein, & YI (2011), I adopt the interest spread rate as the measure of cost of bank debt. The interest spread rate is as the difference between average interest expense and the annual one-year loan prime rate. The average interest expense is measured by the interest expenses reported in the income statement scaled by total debt.

### 4.4.2. Independent variable: Firm-bank Fintech Influence Score

The primary independent variable is the Firm-Bank Fintech Influence Score, which captures the direct impact of banks' Fintech adoption on their client firms. To construct this score, I first calculate the banks' level of Fintech adoption. I extract a range of key terms related to Fintech and digitalization from relevant research and industry reports. These terms are used to evaluate the banks' digitalization across four key dimensions: intelligence, informationalization, internetization, and digitization.

The specific method for constructing the thesaurus of Fintech terms is followed. I manually selected a seed set of keywords from a sample of 30 Chinese banks' annual reports from 2011 to 2021. This seed set serves as the foundational layer for identifying relevant Fintech concepts. To expand this set, I employ Word2Vec, a robust natural language processing technique that leverages neural networks to generate dense vector representations of words. By training Word2Vec on a large corpus of financial documents, the model learns to capture the semantic relationships between words, placing semantically similar words closer together in the vector space. This capability allows to input the initial seed keywords and identify a broader range of synonyms, related terms, and variations that are contextually relevant to Fintech. Word2Vec's ability to compute the similarity between words and perform analogical reasoning ensures that the expanded keyword set maintained high relevance and accuracy. For instance, Word2Vec can identify patterns such as "blockchain" being related to "cryptocurrency" and "API" being related to "integration," enriching the thesaurus with terms that share analogous relationships. This approach not only enhances the comprehensiveness of our keyword set but also ensures its scalability and contextual accuracy. I have included a table of sample key words in the Appendix C2.

Second, I use the thesaurus of Fintech terms to construct the bank level Fintech adoption index, which is calculated based on the frequency of key terms in banks' annual reports. Specifically, I employ the Term Frequency-Inverse Document Frequency (TF-IDF) method, and it is constructed in the following way:

$$
\begin{aligned}
&Fintech\_TFIDF_{t,b} \\
&\qquad = \sum The\ frequency\ of\ each\ key\ word\ in\ an\ annual\ report \\
&\qquad \times \ln\left(\frac{Total\ number\ of\ annual\ reports}{Number\ of\ reports\ containing\ the\ key\ word}\right)
\end{aligned}
$$

Third, I adopt the method used in Naiki and Ogane (2024) to determine the loan weight rate for each firm. The loan weight rate $\mathrm{Weight}_{i,b,t}$ refers to the ratio of the loan amount borrowed by firm $i$ from the lending bank $b$ to the total loan amount borrowed by firm $i$ from all banks in year $t$. The equation is as follows:

$$Weight_{i,b,t} = \frac{Bank\ loan_{i,b,t}}{Total\ loan_{i,t}}$$

Finally, the Firm Bank Fintech Influence Score for firm $i$ in year $t$ is calculated by summing the product of the loan weight $\mathrm{Weight}_{i,b,t}$ and the Fintech adoption score $Fintech\_TFIDF_{t,b}$ for each bank $b$ that lends to the firm $i$ .

$$Firm\ Bank\ Fintech\ Influence\ Score_{i,t} = \sum \left(Weight_{i,b,t} \times Fintech\_TFIDF_{t,b}\right)$$

### 4.4.3. Control variables

Following prior research, I include several determinants for cost of bank debt as control variables. I use the natural logarithm of total assets as a proxy for *firm size*. Larger firms typically exhibit lower default risk, which may influence interest costs (Petersen & Rajan, 1994). I use the *natural logarithm of total revenue* as a measure of a firm's overall financial performance and operational scale of the firm, which can influence its borrowing capacity and interest costs. I use the number of years since the firm's inception to measure the *firm's age*. This approach is based on evidence that a firm's maturity can influence its interest costs (Sakai et al., 2010). In addition, *Tobin's Q* defined as the market value of a firm divided by the replacement cost of its assets, is used as a measure of a firm's investment performance. *The price-to-book ratio* (PB) is a measure of the market's valuation of the firm relative to its book value. *Liquidity ratio* measures the firm's ability to meet its short-term obligations. Also, I include province-level macroeconomic variables such as *GDP per capita* and the Consumer Price Index (*CPI*) to account for varying economic conditions across different provinces.

### 4.4.4. Data

I start the sample selection process by gathering all bank loan information for firms listed on the Shanghai and Shenzhen stock exchanges. This data is sourced from the Chinese Research Data Services Platform (CNRDS), a comprehensive database that offers a wide range of financial, economic, and social data for academic research in China. I have excluded firm-year level data in the following cases: 1) when the firm did not fully disclose all its lending banks for that specific year. 2) when the narrative annual reports of the firm's lending banks for that specific year are not available online, making the calculation of the Fintech index infeasible. Also, I eliminate observations with missing values for the cost of debt and with insufficient data on other variables. Other firm-level data used in the study is obtained from CNRDS, while macroeconomic data is sourced from the China Securities Markets and Accounting Research Database (CSMAR). Finally, I obtain 2,159 firm-year observations. The dataset comprises a sample of 972 listed firms in China covering the period of 2011-2022. Table 4.1 provides the descriptive statistics of the variables used in the main analyses.

**Table 4. 1** Descriptive statistics

| Variables | (1) N | (2) mean | (3) s.d. | (4) min | (5) max |
|---|---|---|---|---|---|
| Dependent variable | | | | | |
| COD | 2,159 | 2.986 | 1.299 | 0.609 | 6.000 |
| Independent variable | | | | | |
| FBFTIS | 2,159 | 13.190 | 10.790 | 0 | 35.180 |
| Control variable | | | | | |
| PB | 2,159 | 3.233 | 2.128 | 0.844 | 9.853 |
| Ln (Total revenue) | 2,159 | 21.410 | 1.212 | 19.070 | 24.190 |
| Size | 2,159 | 22.140 | 1.173 | 19.230 | 27.930 |
| Liquid ratio | 2,159 | 2.164 | 1.878 | 0.168 | 23.210 |
| Tobin's Q | 2,159 | 1.959 | 1.224 | 0.777 | 17.680 |
| Firm Age | 2,159 | 2.886 | 0.344 | 0.693 | 3.892 |
| GDP per capita | 2,159 | 8.406 | 3.765 | 1.885 | 19.030 |
| CPI | 2,159 | 2.207 | 0.947 | 0.100 | 6.100 |

Note: This table contains summary statistics of our key variables. I provide a detailed definition of each variable in Appendix C1. All variables are for borrowing firms. I winsorize firm specific control variables at the 1st and 99th percentiles.

# 4.5. Empirical analysis

## 4.5.1. Baseline model

To estimate the relation between borrowing firms' cost of bank debt and their lending banks' Fintech adoption, we construct the following regression model:

$$COD_{i,t} = \alpha_0 + \alpha_1 FBFTIS_{i,t-1} + \sum X_{i,t-1} + \sum PROVMacro_{i,t-1} + YearFE + IndustryFE + ProvinceFE + \varepsilon_{i,t}$$

[1]

The dependent variable, $COD_{i,t}$, is firm $i$'s cost of bank debt in year $t$. The independent variable of interest, $FBFTIS_{i,t-1}$, indicating the level of Fintech impact imposed on borrowing firms by their lending banks. $X_{i,t-1}$ is a vector of firm-level control variables including *firm size, total revenue, firm's age, Tobin's Q, price-to-book ratio* and *liquidity ratio*. $PROVMacro_{i,t-1}$ is a vector of province-level macroeconomic variables, including *GDP per capita* and *CPI*. All continuous firm-level variables are winsorized at the 1st and 99th percentiles. To mitigate reverse causality to some extent, all control and independent variables lag for one year. Also, I add *Year, Province* and *Industry* fixed effects to control for time, regional and industrial dynamics. In all estimations, standard errors are clustered at the firm level.

Table 4.2 shows that, in general, *FBFTIS* has a negative effect on firms' cost of bank debt. Column 4 presents the results with *Year*, *Industry*, and *Province* fixed effects and all control variables, revealing that the estimated coefficient on *FBFTIS* is −0.006, which is significant at the 5% statistical significance level. This translates to a decrease in the cost of debt by approximately 0.061 percentage points, which corresponds to 8.2% of the average firm's cost of bank debt in this sample. Column 2 includes *Industry* and *Year* fixed effects, Column 3 includes *Industry* and *Province* fixed effects and Column 1 removes all control variables and fixed effects. Across these models, the coefficients of *FBFTIS* range from −0.005 to −0.007, consistently showing statistical significance. These results support the argument that firms borrowing from lending banks with a higher level of Fintech adoption have lower borrowing costs. They align with previous evidence suggesting that the adoption of Fintech is beneficial to firms through bank lending practices (He, Geng, Tan, & Guo, 2023; Kutzbach & Pogach, 2024; Wang & Wu, 2024).

**Table 4. 2:** The effect of FBFTIS on COD.

| Variables | (1) $COD_{i,t}$ | (2) $COD_{i,t}$ | (3) $COD_{i,t}$ | (4) $COD_{i,t}$ |
|---|---|---|---|---|
| $FBFTIS_{i,t-1}$ | -0.005* | -0.007** | -0.005** | -0.006** |
| | (-1.89) | (-2.27) | (-2.11) | (-2.18) |
| $Ln\ (Total\ revenue)_{i,t-1}$ | | -0.289*** | -0.332*** | -0.346*** |
| | | (-4.36) | (-5.24) | (-5.38) |
| $Tobin's\ Q_{i,t-1}$ | | -0.145*** | -0.117*** | -0.107*** |
| | | (-4.35) | (-3.77) | (-3.35) |
| $PB_{i,t-1}$ | | 0.054** | 0.046** | 0.042** |
| | | (2.44) | (2.24) | (2.07) |
| $Firm\ Age_{i,t-1}$ | | 0.305** | 0.238** | 0.222* |
| | | (2.41) | (1.96) | (1.91) |
| $Liquid\ ratio_{i,t-1}$ | | -0.181*** | -0.179*** | -0.182*** |
| | | (-6.80) | (-6.69) | (-6.63) |
| $Size_{i,t-1}$ | | 0.233*** | 0.274*** | 0.283*** |
| | | (3.21) | (4.03) | (4.09) |
| $CPI_{i,t-1}$ | | 0.171** | 0.177*** | 0.144** |
| | | (2.32) | (2.69) | (2.13) |
| $GDP\ per\ capita_{i,t-1}$ | | 0.082** | -0.012 | 0.079** |
| | | (2.05) | (-1.29) | (2.05) |
| Constant | -2.913*** | -3.280*** | -2.362*** | -2.909*** |
| | (-59.45) | (-3.54) | (-2.70) | (-3.07) |
| *Province FE* | NO | YES | NO | YES |
| *Year FE* | NO | YES | YES | YES |
| *Industry FE* | NO | NO | YES | YES |
| Observations | 2,382 | 2,159 | 2,159 | 2,159 |
| R-squared | 0.300 | 0.317 | 0.394 | 0.415 |

Note: This table presents estimates from the baseline regression model examining the relationship between firm-bank Fintech Influence Score (*FBFTIS*) and firms' cost of debt (*COD*). The dependent variable is the *COD*, measured by subtracting the average one-year loan rate from the average interest rate. The main variable of interest is *FBFTIS*. Column 1 removes all the control variables and fixed effects. Columns 2 and 3 explore variations in fixed effects, with Column 2 including *Province* and *Year* fixed effects, and Column 3 including *Industry* and *Year* fixed effects. Column 4 includes *Year, Industry,* and *Province* fixed effects, as well as all control variables, such as *Ln*(*total revenue), Tobin's q*, *Liquidity ratio, Firm Size, Firm Age*, *Price-to-Book Ratio*, *CPI*, and *GDP per Capita*. All explanatory variables lag by one year. Standard errors are clustered at the firm level and reported in parentheses beneath coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

## 4.5.2. Robustness test

### 4.5.2.1 Alternative measure of the dependent variable

In this section, I employ an alternative method to calculate the cost of bank debt. In the main regression analysis, the cost of bank debt is determined by subtracting the average one-year loan rate from the average interest rate. Here, I replace the average one-year loan rate with the average five-year loan rate to capture the longer-term risk-free rate (Chen, 2019; Reiter & Zessner-Spitzenberg, 2023). Table 4.3 demonstrates that, overall, these results are consistent with the main findings. Specifically, the coefficient of *FBFTIS* that controls for all fixed effects—*Province, Industry,* and *Year*—decreases from -0.006 to -0.008. The coefficient of *FBFTIS* controlling for *Province* and *Year* fixed effects decreases from -0.007 to -0.009. Meanwhile, the coefficient of *FBFTIS* controlling for *Industry* and *Year* fixed effects decreases from -0.005 to -0.008.

**Table 4. 3** Alternative dependent variable measure

| Variables | (1)<br>$COD_{i,t}$ | (2)<br>$COD_{i,t}$ | (3)<br>$COD_{i,t}$ |
|---|---|---|---|
| $FBFTIS_{i,t-1}$ | -0.008*** | -0.009*** | -0.008*** |
| | (-2.68) | (-2.67) | (-2.59) |
| $Ln\ (Total\ revenue)_{i,t-1}$ | -0.487*** | -0.407*** | -0.462*** |
| | (-4.73) | (-4.10) | (-4.40) |
| $Tobin's\ Q_{i,t-1}$ | -0.122*** | -0.163*** | -0.141*** |
| | (-2.91) | (-3.68) | (-3.34) |
| $PB_{i,t-1}$ | 0.051** | 0.072*** | 0.057** |
| | (2.10) | (2.59) | (2.20) |
| $Firm\ Age_{i,t-1}$ | 0.087 | 0.227 | 0.154 |
| | (0.54) | (1.41) | (0.93) |
| $Liquid\ ratio_{i,t-1}$ | -0.285*** | -0.272*** | -0.276*** |
| | (-3.63) | (-3.69) | (-3.58) |
| $Size_{i,t-1}$ | 0.389*** | 0.320*** | 0.366*** |
| | (3.51) | (3.08) | (3.13) |
| $CPI_{i,t-1}$ | -0.010 | 0.050 | 0.059 |
| | (-0.07) | (0.36) | (0.48) |
| $GDP\ per\ capita_{i,t-1}$ | 0.155** | 0.151** | -0.032** |
| | (2.34) | (2.37) | (-2.16) |
| Constant | -2.210 | -2.893** | -0.998 |

| | | | |
|---|---|---|---|
| | (-1.58) | (-2.18) | (-0.68) |
| *Province FE* | YES | YES | NO |
| *Year FE* | YES | YES | YES |
| *Industry FE* | YES | NO | YES |
| Observations | 2,159 | 2,159 | 2,159 |
| R-squared | 0.322 | 0.247 | 0.295 |

Note: This table presents estimates from a regression model examining the relationship between *FBFTIS* and firms' *COD*. The dependent variable is the *COD* using an alternative measure (subtracting the average five-year loan rate from the average interest rate). The main variable of interest is *FBFTIS*. Column 1 includes *Year, Industry,* and *Province* fixed effects, as well as all control variables. Columns 2 and 3 explore variations in fixed effects, with Column 2 including *Province* and *Year* fixed effects, and Column 3 including *Industry* and *Year* fixed effects. All explanatory variables lag by one year. Standard errors are clustered at the firm level and reported in parentheses beneath coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

#### 4.5.2.2 Additional bank-level weighted controls

In this section, I consider several significant bank-specific characteristics in determining loan costs for borrowing firms following previous literature (Berger & Humphrey, 1997; Athanasoglou, Brissimis, & Delis, 2008; Berger & Humphrey, 1997; Demirgüç-Kunt & Huizinga, 1999). To do so, I add bank-level weighted variables to the baseline regression. Following a similar approach to calculating the *FBFTIS*, I use the loan weight rate multiplied by bank size, bank revenue, bank ROA and bank asset turnover to obtain the weighted averages of bank size, bank revenue, and bank asset turnover. Table 4.4 presents the results, which are in line with the main analysis. Specifically, the coefficient of *FBFTIS* that controls all fixed effects decreases from -0.006 to -0.007. The coefficient of *FBFTIS* controlling for *Province* and *Year* fixed effects decreases from -0.007 to -0.008. Meanwhile, the coefficient of *FBFTIS* controlling for *Industry* and *Year* fixed effects decreases from -0.005 to -0.006.

**Table 4. 4:** Additional controls

| Variables | (1) $COD_{i,t}$ | (2) $COD_{i,t}$ | (3) $COD_{i,t}$ |
|---|---|---|---|
| $FBFTIS_{i,t-1}$ | -0.007** | -0.008** | -0.006** |
| | (-2.26) | (-2.58) | (-2.23) |
| $Ln\ (Total\ revenue)_{i,t-1}$ | -0.344*** | -0.288*** | -0.331*** |
| | (-5.33) | (-4.30) | (-5.21) |
| $Tobin's\ Q_{i,t-1}$ | -0.107*** | -0.146*** | -0.115*** |
| | (-3.33) | (-4.36) | (-3.75) |
| $PB_{i,t-1}$ | 0.042** | 0.054** | 0.046** |
| | (2.07) | (2.45) | (2.24) |
| $Firm\ Age_{i,t-1}$ | 0.225* | 0.306** | 0.241** |
| | (1.94) | (2.42) | (1.99) |
| $Liquid\ ratio_{i,t-1}$ | -0.182*** | -0.182*** | -0.180*** |
| | (-6.63) | (-6.80) | (-6.68) |
| $Size_{i,t-1}$ | 0.285*** | 0.236*** | 0.276*** |
| | (4.09) | (3.25) | (4.04) |
| $CPI_{i,t-1}$ | 0.139** | 0.170** | 0.170*** |
| | (2.06) | (2.30) | (2.59) |
| $GDP\ per\ capita_{i,t-1}$ | 0.079** | 0.082** | -0.012 |
| | (2.07) | (2.05) | (-1.30) |
| $weighted\ bank\ ROE_{i,t-1}$ | -0.007 | -0.001 | -0.009 |
| | (-1.14) | (-0.19) | (-1.36) |
| $weighted\ bank\ size_{i,t-1}$ | -0.014 | -0.018 | -0.018 |
| | (-0.17) | (-0.20) | (-0.22) |
| $weighted\ bank\ total\ revenue_{i,t-1}$ | 0.012 | 0.016 | 0.017 |
| | (0.13) | (0.15) | (0.18) |
| $weighted\ bank\ asset\ turnover_{i,t-1}$ | 4.312 | 5.789 | 4.080 |
| | (0.70) | (0.84) | (0.64) |
| *Constant* | -2.960*** | -3.369*** | -2.390*** |
| | (-3.13) | (-3.62) | (-2.74) |
| *Province FE* | YES | YES | NO |
| *Year FE* | YES | YES | YES |
| *Industry FE* | YES | NO | YES |
| *Observations* | 2,159 | 2,159 | 2,159 |
| *R-squared* | 0.416 | 0.318 | 0.396 |

Note: This table presents estimates from a regression model examining the relationship between *FBFTIS* and firms' *COD* with additional weighted average of bank-level controls. The dependent variable is *COD*. The main variable of interest is *FBFTIS*. Column 1 includes *Year, Industry*, and *Province* fixed effects, as well as all control variables. Columns 2 and 3 explore variations in fixed effects, with Column 2 including *Province* and *Year* fixed effects, and Column 3 including *Industry* and *Year* fixed effects. All explanatory variables lag by one year. Standard errors are clustered at the firm level and reported in parentheses beneath coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

#### 4.5.2.3 Self-selection bias

When conducting the empirical analysis of the relationship between the Firm-bank Fintech Influencing Score (*FBFTIS*) and the Cost of Debt (*COD*), there is a potential endogeneity issue. This issue arises because the samples in the dataset are not randomly selected; only firms that apply for and ultimately obtain bank loans are included in the sample. The sample may not be representative, as firms that choose to borrow exhibit specific advantageous characteristics, such as a strong credit history, stable cash flow, or higher technological capacity. These characteristics can act as unobserved confounding factors that lead to endogeneity, potentially affecting firms' borrowing costs. As a result, the cost of debt for firms that do not apply for or receive loans remains unobserved, which can skew the analysis. To address this selection bias, I employ the Heckman two-stage model (1979).

**First Stage regression**

The first stage of the Heckman test examines the probability of companies obtaining bank loans using the following probit regression as the selection model:

$$\begin{aligned} Loandummy_{i,t} &= \beta_0 + \beta_1 FBFTIS_{i,t-1} + \beta_2 Loandummy_{i,t-2} + \sum X_{i,t-1} \\ &+ \sum PROVMacro_{i,t-1} + YearFE + IndustryFE + ProvenceFE \\ &+ \pi_{i,t} \end{aligned}$$

[2]

Where $Loandummy_{i,t}$ is a dummy indicator that equals 1 if company $i$ obtains bank loans in year $t$, and equals 0 otherwise. $FBFTIS_{i,t-1}$ is the core independent variable. The vector $X_{i,t-1}$ represents the set of control variables used in the second-stage model and the baseline model. All explanatory variables in the first and second stages lag by one period. According to Lennox, Francis & Wang (2012), when using the Heckman two-stage model, it is necessary to introduce exclusion restrictions. These are variables that are assumed to have no direct effect on the dependent variable but have an indirect effect via the inverse Mills ratio (IMR). This ensures that the exclusion restriction variable is not related to the residual of the baseline model. The exclusion restriction variable I chose here is $Loandummy_{i,t-2}$, a two-period lag $Loandummy_{i,t}$, indicating whether the company obtained bank loans in the previous two periods. $Loandummy_{i,t-2}$ can be an exclusion restriction because 1) it meets the requirements of exogeneity. This dummy variable represents a state or characteristic from the previous period, and it does not directly affect the loan rate for the current period. The two-year lag provides temporal distance, which reduces the likelihood that the past loan will influence the current cost of bank debt. The financial conditions that justified the previous loan are no longer relevant, as both the company's circumstances and the overall economic environment may have changed significantly. Consequently, the terms of the past loans do not directly affect current borrowing costs. 2) it meets the requirement of high correlation $Loandummy_{i,t}$. The fact that a company received a bank loan two years ago is relevant to its current decision to seek or receive a loan. This historical borrowing behavior can indicate the company's established relationship with the bank and its creditworthiness, both of which are important factors in the selection process.

**Second-stage model**

The second stage of the Heckman test estimates the following outcome model incorporating the inverse Mills ratio (IMR) from the first stage to correct for sample selection bias.

$$COD_{i,t} = \gamma_0 + \gamma_1 FBFTIS_{i,t-1} + \gamma_3 IMR + \sum X_{i,t-1} + \sum PROVMacro_{i,t-1} + YearFE + IndustryFE + ProvenceFE + \mu_{i,t}$$

[3]

Table 4.5 presents the results of the Heckman test. Column (1) displays the findings from the first-stage selection equation. The estimated coefficient for the exogenous variable, $Loandummy_{i,t-2}$, is significantly positive at the 1% level, indicating the validity of this variable in the selection process. This positive coefficient suggests that firms with a history of borrowing are more likely to obtain loans again, highlighting the importance of maintaining an ongoing banking relationship in accessing credit. This finding is consistent with the research by Behr and Sonnekalb (2012). Additionally, a positive coefficient for FBFTIS indicates that higher Fintech influence scores increase the likelihood of a firm obtaining a loan, suggesting that banks with strong Fintech capabilities are more willing to lend. Column (2) presents the results of the second-stage outcome model. The coefficient of the *IMR* is significant at the 1% level, indicating that the sample selection bias in the model cannot be ignored. Furthermore, a negative coefficient for $FBFTIS_{i,t-1}$ indicates that higher Fintech influence reduces borrowing costs. This supports the notion that banks' adoption of Fintech can lower the cost of bank debt for borrowing firms. The results of the baseline model remain consistent when selection bias is taken into account.

**Table 4. 5:** Heckman test

| Variables | (1)<br>First<br>$Loandummy_{i,t}$ | (2)<br>Second<br>$COD_{i,t}$ |
|---|---|---|
| $FBFTIS_{i,t-1}$ | 0.006* | -0.009*** |
| | (1.75) | (-2.82) |
| $Loandummy_{i,t-2}$ | 0.423*** | |
| | (6.05) | |
| $Liquid\ ratio_{i,t-1}$ | -0.054** | -0.160*** |
| | (-2.53) | (-5.08) |

| | | |
|---|---|---|
| $Ln\ (Total\ revenue)_{i,t-1}$ | 0.065 | -0.373*** |
| | (1.13) | (-5.39) |
| $PB_{i,t-1}$ | -0.033 | 0.062*** |
| | (-1.24) | (2.70) |
| $Size_{i,t-1}$ | -0.090 | 0.293*** |
| | (-1.49) | (3.95) |
| $Tobin's\ Q_{i,t-1}$ | 0.003 | -0.132*** |
| | (0.07) | (-3.74) |
| $Firm\ Age_{i,t-1}$ | -0.027 | 0.238* |
| | (-0.24) | (1.90) |
| $CPI_{i,t-1}$ | 0.006 | 0.129* |
| | (0.06) | (1.85) |
| $GDP\ per\ capita_{i,t-1}$ | -0.089** | 0.100** |
| | (-2.13) | (2.24) |
| $IMR$ | | -0.535*** |
| | | (-3.41) |
| *Constant* | 1.083 | -2.040* |
| | (0.97) | (-1.91) |
| *Province FE* | YES | YES |
| *Year FE* | YES | YES |
| *Industry FE* | YES | YES |
| *Observations* | 1,891 | 1,902 |
| *R-squared* | | 0.357 |
| *Pseudo R-squared* | 0.1098 | |

Note: This table illustrates the estimates of the hackmen test which relieves self-selection bias. Column 1 shows the estimates of the first stage regression. Column 2 shows the estimates of the second stage regression. The set of control variables used in the baseline model are applied in both stages and include *Year, Industry*, and *Province* fixed effects. All explanatory variables in the first and second stages lag by one stage. Standard errors are clustered at the firm level and reported in parentheses beneath coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

#### 4.5.2.4 Endogeneity

Despite the controls lagging by one period, the results may still suffer from endogeneity problems caused by reverse causality. For example, banks with higher levels of Fintech development may prefer firms with lower risk, which could lead to lower cost of debt.

To address this problem, I have adopted two approaches. Firstly, I use a two-stage least squares regression with instrumental variables for my core independent variable

(*FBFTIS*). The instrumental variables I employ are the total number of FinTech startup companies in the banks' headquarter city each year (*Total Fintech*) and the annual growth in the number of FinTech startup companies (*Growth Fintech*). The total number of Fintech startup companies can capture the long-term impact of Fintech startups on banks, while the annual growth in the number of Fintech startup companies reflects the dynamic changes and development speed of FinTech startups in the city where the bank is located. A higher number of annually growing Fintech startups and a larger total number of FinTech startups are highly positively correlated with *FBFTIS*. This indicates that banks are more likely to establish partnerships with Fintech startup companies in the region, suggesting a higher level of Fintech integration for the bank. Moreover, a firm's cost of debt is less likely to be correlated with the number of Fintech startups in the city where its lending banks are headquartered.

It may be argued that when the borrower firm is located in the same city as its lending banks, the firm's cost of debt may be influenced by the number of Fintech startups. This is because the presence of Fintech startups can lead to increased competition in the financial sector, which potentially decreases the loan interest rate. However, this does not necessarily violate the assumption of exogeneity for instrument variables. Non-bank financial institutions, including Fintech startups, typically charge higher loan interest rates than banks due to the higher level of credit risk they face. This increased risk of default necessitates higher interest rates to compensate for potential losses and ensure profitability (Chernenko, Erel, & Prilmeier, 2018). Therefore, Fintech startups compete with banks primarily in terms of efficiency and do not directly lead to a reduction in the cost of debt for listed firms.

Table 4.6 presents the results of the 2SLS regression. In the first stage, I employ *FBFTIS* as the dependent variable. The Cragg-Donald Wald F-statistic value is larger than the critical value provided by Stock and Yogo (2005), which leads to the rejection of the null hypothesis that the instruments are weak. The F-value of Kleibergen-Paap rk LM statistic is greater than 10 and the P-value is less than 0.01, which rejects the null hypothesis that the instruments are underidentified. In the second stage, the coefficients of the FBFTIS are significantly negative, which is in line with the baseline model. The Hansen J statistic shows that the overidentifying restrictions are valid. All the control variables are also included in the first-stage regression and I also control for *Province, Industry* and *Year* fixed effects. The standard errors are clustered at the firm level.

**Table 4. 6:** 2SLS regression

| Variables | (1)<br>Second stage<br>$COD_{i,t}$ | (2)<br>First stage<br>$FBFTIS_{i,t}$ |
|---|---|---|
| $FBFTIS_{i,t-1}$ | -0.016* | |
| | (-1.84) | |
| $Total\ Fintech_{i,t-1}$ | | 0.001*** |
| | | (3.50) |
| $Growth\ Fintech_{i,t-1}$ | | 0.004*** |
| | | (3.37) |
| $Ln\ (Total\ revenue)_{i,t-1}$ | -0.340*** | 0.202 |
| | (-5.27) | (0.48) |
| $Tobin's\ Q_{i,t-1}$ | -0.113*** | -0.491* |
| | (-3.47) | (-1.95) |
| $PB_{i,t-1}$ | 0.042** | -0.009 |
| | (2.05) | (-0.06) |
| $Firm\ Age_{i,t-1}$ | 0.222* | -0.257 |
| | (1.94) | (-0.35) |
| $Liquid\ ratio_{i,t-1}$ | -0.181*** | 0.038 |
| | (-6.63) | (0.40) |
| $Size_{i,t-1}$ | 0.273*** | -1.013** |
| | (3.90) | (-2.08) |
| $CPI_{i,t-1}$ | 0.141** | -0.210 |
| | (0.068) | (0.535) |
| $GDP\ per\ capita_{i,t-1}$ | 0.085** | 0.650*** |
| | (0.038) | (0.237) |
| Constant | | 25.052*** |
| | | (3.68) |
| *Kleibergen-Paap rk LM statistic* | | 0.000 |
| *Cragg-Donald Wald F statistic* | | 102.282 |
| *Hansen J statistic* | 0.670 | |
| *Province FE* | YES | YES |
| *Year FE* | YES | YES |
| *Industry FE* | YES | YES |

| | | |
|---|---|---|
| *Observations* | 2,159 | 2,159 |
| *R-squared* | 0.116 | 0.418 |

Note: This table shows the estimates of the 2SLS regression. Column 1 shows the estimates of the second stage regression. Column 2 shows the estimates of the first stage regression. The set of control variables used in the baseline model are applied in both stages and include Year, Industry, and Province fixed effects. All explanatory variables in the first and second stages lag by one stage. Standard errors are clustered at the firm level and reported in parentheses beneath coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Secondly, I re-estimate the effect of bank Fintech development on a firm's cost of debt using the Difference-in-Differences (DID) method. The DID treatment I employ is a policy initiated in December 2010 by the Ministry of Science and Technology of China, which promotes pilot cities to encourage practical activities for technological and financial innovation in pilot areas. Based on this policy, the first batch of pilot regions for science and technology finance was established in October 2011. This included Tianjin, Jiangsu Province, and a total of 16 regions (comprising 41 cities). A second batch of pilot cities was added in June 2016, including cities such as Zhengzhou, Xiamen, and Ningbo, totaling 9 additional cities. As a result, a total of 50 cities were included within the scope of the policy.

The results in Table 4.7 above show that the policy of Fintech pilot cities has a significant negative impact on firms’ cost of debt, which is in line with the baseline model. Also, I conduct the parallel trend test. The results of the parallel trend test (Figure 4.1) indicate that the treatment and control groups have followed similar trends in the outcome variable, cost of debt, prior to the policy implementation, while there is a significant difference between the two groups in the post-policy period.

**Table 4. 7:** DID regression:

| Variables | (1) $COD_{i,t}$ |
|---|---|
| $Post_t$ | -0.119*** |
| | (-2.70) |
| $Ln\ (Total\ revenue)_{i,t}$ | -0.263*** |
| | (-7.93) |
| $Tobin's\ Q_{i,t}$ | -0.018* |
| | (-1.92) |
| $PB_{i,t}$ | -0.013* |
| | (-1.85) |
| $Firm\ Age_{i,t}$ | 0.210*** |
| | (3.97) |
| $Liquid\ ratio_{i,t}$ | -0.077*** |
| | (-6.07) |
| $Size_{i,t}$ | 0.350*** |
| | (11.22) |
| $CPI_{i,t}$ | 0.006 |
| | (0.37) |
| $GDP\ per\ capita_{i,t}$ | 0.068*** |
| | (5.47) |
| *Constant* | -6.009*** |
| | (-12.54) |
| *Province FE* | YES |
| *Year FE* | YES |
| *Industry FE* | YES |
| *Observations* | 28,544 |
| *R-squared* | 0.334 |

Note: This table shows the estimates of the DID analysis. *Post* is a dummy variable that takes the value of 1 after the policy implementation and 0 otherwise. The set of control variables used in the baseline model are applied and include *Year, Industry*, and *Province* fixed effects. Standard errors are clustered at the firm level and reported in parentheses beneath coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

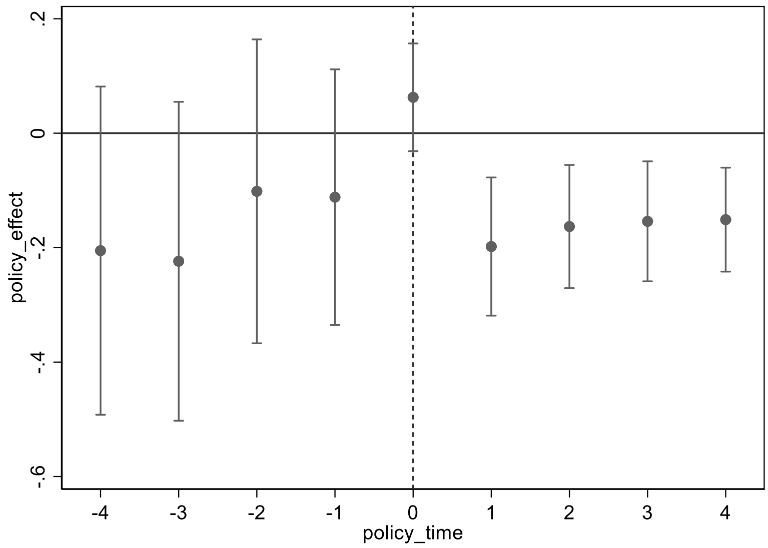



Figure 4.1. Parallel trend test

Note: This figure reports a multi-period DID parallel trend test, using a 95% confidence interval where the dependent variable is cost of debt.

## 4.6. Further tests on the mechanisms

Hitherto, I have found evidence that an increased adoption of Fintech by lending banks significantly decreases the cost of bank debt for borrowing firms. To further understand the nature and potential drivers of this result, I consider the potential channels that might be driving the negative effect of Fintech adoption on the cost of debt for firms. I ask whether the cost of bank debt for borrowing firms decreases with the adoption of Fintech by lending banks through the channels of information asymmetries, particularly by reducing adverse selection and moral hazard. Also, I test several other mechanisms.

### 4.6.1. Fintech and the reduction of adverse selection

#### 4.6.1.1 Firms lacking information cues

Previous literature and empirical studies document that hidden information and adverse selection are more pronounced in firms that are informationally opaque to banks, such as private or small firms. This often leads to higher adverse selection costs for these firms, which are frequently forced to resort to more expensive credit sources (Brandt &

Li, 2003). In contrast, banks tend to favor borrowers with more reliable information sources, such as those with strong bank backgrounds and better auditing practices. These characteristics typically indicate higher regulatory compliance, transparency, and less hidden information for banks (Gallimberti, 2021; Wang & Wang, 2024). However, Fintech algorithms have significantly reduced hidden information in loans by leveraging advanced data analytics and machine learning to provide more objective and comprehensive assessments of creditworthiness. This technological advancement has the potential to lower adverse selection costs for firms that were previously less transparent to banks (Bartlett, 2018). Therefore, I test whether the adoption of Fintech by lending banks reduces adverse selection costs for firms that are not traditionally favored in bank lending due to a lack of information cues, ultimately resulting in a lower cost of bank debt.

To provide evidence on this, I re-do the baseline regression using several subsamples that exclude those borrowers with higher informational proximity to banks. Tabel 4.8 shows the result of the regressions. Column (1) and (2) show the regression results with subsamples that exclude firms that are audited by the Big 4 accounting firms (Deloitte, PwC, EY, and KPMG), and those invested by banks, respectively. Column (3) shows the result with a subsample that excludes both the two types of firms. The results are similar when considering the entire sample of observations. This analysis highlights the reduction in adverse selection costs for firms lacking information cues due to banks' Fintech development.

**Table 4. 8:** Exclude Big 4 audited and bank invested firms.

| Variables | (1)<br>$COD_{i,t}$<br>Non-Big4 | (2)<br>$COD_{i,t}$<br>Non-Bank Invest | (3)<br>$COD_{i,t}$<br>Not both two types |
|---|---|---|---|
| $FBFTIS_{i,t-1}$ | -0.006** | -0.006** | -0.006** |
| | (-2.12) | (-2.27) | (-2.23) |
| $Ln\ (Total\ revenue)_{i,t}$ | -0.371*** | -0.379*** | -0.392*** |
| | (-5.28) | (-5.50) | (-5.52) |

| | | | |
|---|---|---|---|
| $Tobin's\ Q_{i,t-1}$ | -0.098*** | -0.093*** | -0.089*** |
| | (-2.95) | (-3.02) | (-2.82) |
| $PB_{i,t-1}$ | 0.040* | 0.034* | 0.035* |
| | (1.91) | (1.73) | (1.71) |
| $Firm\ Age_{i,t-1}$ | 0.186 | 0.167 | 0.137 |
| | (1.56) | (1.45) | (1.15) |
| $Liquid\ ratio_{i,t-1}$ | -0.179*** | -0.179*** | -0.175*** |
| | (-6.59) | (-6.54) | (-6.48) |
| $Size_{i,t-1}$ | 0.326*** | 0.329*** | 0.356*** |
| | (3.99) | (4.24) | (4.29) |
| $CPI_{i,t-1}$ | 0.169** | 0.156** | 0.183** |
| | (2.34) | (2.28) | (2.57) |
| $GDP\ per\ capita_{i,t-1}$ | 0.079* | 0.087** | 0.084** |
| | (1.95) | (2.14) | (2.02) |
| *Constant* | -3.272*** | -3.125*** | -3.412*** |
| | (-3.12) | (-3.25) | (-3.30) |
| *Province FE* | YES | YES | YES |
| *Year FE* | YES | YES | YES |
| *Industry FE* | YES | YES | YES |
| *Observations* | 2,063 | 2,053 | 1,974 |
| *R-squared* | 0.417 | 0.417 | 0.420 |

Note: This table presents the results for firms lacking information cues. Column (1) and (2) show the regression results with subsamples that exclude firms that are audited by the Big 4 accounting firms (Deloitte, PwC, EY, and KPMG), and those invested by banks, respectively. Column (3) shows the result with a subsample that excludes both these two types of firms. The set of control variables used in the baseline model are applied and include *Year, Industry,* and *Province* fixed effects. All explanatory variables lag by one stage. Standard errors are clustered at the firm level and reported in parentheses beneath coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

#### 4.6.1.2 Firms with financial constraints

In addition, financially constrained firms experienced a greater increase in the cost of bank financing during the 2008 financial crisis, as documented by Albuquerque (2024). This increase is partly due to the perception that financially constrained firms are seen as less transparent and more likely to hide company-specific information. Financially constrained firms often conceal information to protect competitive advantages, avoid negative publicity, and reduce regulatory scrutiny, which in turn leads to higher levels of information asymmetry and adverse selection-related borrowing costs (Kurt, 2018).

Linn & Weagley (2024) further find that these firms are more sensitive to shocks in the cost of equity and debt financing. Hence, I investigate whether the adoption of Fintech by lending banks can alleviate the level of adverse selection against borrowing firms with higher levels of financial constraints, thereby reducing their cost of bank loans.

To do so, I test whether the negative relationship between *FBFTIS* and *COD* depends on the financial constraints level. I use the Kaplan-Zingales (KZ) index as the proxy of the level of financial constraints. The KZ index is a widely used measure of a company's financial constraints, specifically its dependence on external financing. It was proposed by Kaplan and Zingales in 1997. A higher KZ index indicates greater financial constraints. Then, I add the KZ index into the baseline regression as an interaction item and form the following model:

$$
\begin{aligned}
COD_{i,t} = \delta_0 + \delta_1 KZ_{i,t-1} * FBFTIS_{i,t-1} + \delta_2 FBFTIS_{i,t-1} + \delta_3 KZ_{i,t-1} + \sum X_{i,t-1} \\
+ \sum PROVMacro_{i,t-1} + YearFE + IndustryFE + ProvinceFE \\
+ \varphi_{i,t}
\end{aligned}
$$

[4]

The *KZ* index lags for one period as do other variables on the right side. The coefficient of the interaction term ($\pi_1$) shows how the negative relationship between $FBFTIS$ and firms' $COD$ varies across the level of financial constraints of firms. Table 4.9 presents the results. Column (1) controls for $Year, Industry\ and\ Province$ fixed effect, while column (2) controls for $Year$ and $Province$ fixed effect and column (3) controls for $Year$ and $Industry$ fixed effect. I include all control variables in the three columns.

The estimates suggest that the coefficients of the interaction term are significantly negative at the 5% level, suggesting that the higher KZ index enlarges the negative relationship between lending banks' Fintech development and borrowing firms' cost of debt. Specifically, for each unit increase in the interaction between FBFTIS and the KZ index, the $COD$ decreases by 0.002 to 0.003. In other words, for firms suffering from a higher level of financial constraints, the negative relationship between $FBFTIS$ and firms' $COD$ is more pronounced. This analysis highlights the reduction of adverse selection costs for firms with financial constraints due to banks' Fintech development.

**Table 4. 9:** The effect of Fintech constraints

| Variables | (1)<br>$COD_{i,t}$ | (2)<br>$COD_{i,t}$ | (3)<br>$COD_{i,t}$ |
|---|---|---|---|
| $KZ_{i,t-1} * FBFTIS_{i,t-1}$ | -0.002** | -0.003** | -0.002** |
| | (-2.26) | (-2.28) | (-2.22) |
| $FBFTIS_{i,t-1}$ | -0.001 | -0.002 | -0.001 |
| | (-0.51) | (-0.61) | (-0.43) |
| $KZ_{i,t-1}$ | 0.200*** | 0.199*** | 0.201*** |
| | (8.72) | (8.23) | (8.76) |
| $Ln\ (Total\ revenue)_{i,t-1}$ | -0.302*** | -0.234*** | -0.282*** |
| | (-4.94) | (-3.67) | (-4.68) |
| $Tobin's\ Q_{i,t-1}$ | -0.144*** | -0.173*** | -0.152*** |
| | (-4.57) | (-5.80) | (-4.91) |
| $PB_{i,t-1}$ | 0.039** | 0.049** | 0.042** |
| | (2.00) | (2.45) | (2.14) |
| $Firm\ Age_{i,t-1}$ | 0.131 | 0.196 | 0.147 |
| | (1.16) | (1.57) | (1.27) |
| $Liquid\ ratio_{i,t-1}$ | -0.103*** | -0.102*** | -0.101*** |
| | (-4.31) | (-4.39) | (-4.34) |
| $Size_{i,t-1}$ | 0.249*** | 0.166** | 0.232*** |
| | (3.77) | (2.30) | (3.60) |
| $CPI_{i,t-1}$ | 0.125* | 0.156** | 0.167** |
| | (1.85) | (2.16) | (2.57) |
| $GDP\ per\ capita_{i,t-1}$ | 0.057 | 0.061 | -0.008 |
| | (1.50) | (1.50) | (-0.91) |
| *Constant* | -2.992*** | -2.849*** | -2.641*** |
| | (-3.31) | (-3.17) | (-3.23) |
| *Province FE* | YES | YES | NO |
| *Year FE* | YES | YES | YES |
| *Industry FE* | YES | NO | YES |
| *Observations* | 2,159 | 2,159 | 2,159 |
| *R-squared* | 0.456 | 0.363 | 0.438 |

Note: This table presents the results for *FBFTIS*, *KZ* index and firms' *COD*. Column 1 includes *Year, Industry*, and *Province* fixed effects, as well as all control variables. Columns 2 and 3 explore variations in fixed effects, with Column 2 including *Province* and *Year* fixed effects, and Column 3 including *Industry* and *Year* fixed effects. All explanatory variables lag by one year. Standard errors are clustered at the firm level and reported in parentheses beneath coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Accordingly, I argue that reducing adverse selection is a plausible channel through which the adoption of Fintech by lending banks lowers the cost of bank debt for borrowing firms. This effect is particularly pronounced for firms that are information-biased, such as firms that are not audited by the Big 4 accounting firms, and those without bank investment. Additionally, financially constrained firms are likely to benefit more from this reduction in adverse selection.

## 4.6.2. Fintech adoption reduces moral hazard

### 4.6.2.1 Firms with lower risk taking

Previous literature establishes that moral hazard is a significant concern, particularly in firms that engage in aggressive risk-taking behaviors after receiving loans. Information asymmetry often limits banks' access to insider information regarding firms' risk preferences (Belhaj, Bourlès, & Deroïan, 2014; Cvitanić, Possamaï, & Touzi, 2017). Consequently, banks may impose higher interest rates on borrowing firms to mitigate the risks associated with excessive risk-taking. The adoption of Fintech can alleviate this concern. By leveraging alternative data and advanced data analysis techniques, such as AI algorithms, banks can more accurately assess a customer's risk preferences, potentially offering lower loan rates (Jagtiani & Lemieux, 2019). Therefore, I propose that advancements in banks' Fintech capabilities can reduce firms' cost of bank debt by enabling banks to better understand and manage the risk-taking behaviors of borrowing firms.

To do the test, I estimate whether for firms with higher risk-taking behaviors, the negative relationship between $FBFTIS$ and $COD$ is more pronounced. I use two proxies for firms' risk-taking behaviors: $\sigma(stock\ return)$ (standard deviation of the stock return) and $\sigma(ROA)$ (standard deviation of ROA). I conduct two subsample analyses:

one for borrowing firms with high (above-median) and low (below-median) levels of $\sigma(stock\ return)$, and another for borrowing firms with high (above-median) and low (below-median) levels of $\sigma(ROA)$. To capture the idea of after-lending, I take one year forward in both $\sigma(stock\ return)$ and $\sigma(ROA)$. All the standard errors are clustered at the firm level.

As shown in columns (1), (2), and (3) of Panel A in Table 4.10, for borrowing firms with lower after-lending $\sigma(stock\ return)$, the *FBFTIS* has a significantly negative association with *COD*. However, for borrowing firms with higher after-lending $\sigma(stock\ return)$ in column (4), (5) and (6), the negative association remains, but the significance is lost. Panel B of Table 4.10 shows similar results when firms' risk-taking behavior is measured by $\sigma(ROA)$. Therefore, firms with lower risk-taking are endowed with lower cost of bank debt when the lending banks possess a higher level of Fintech.

**Table 4. 10 (Panel A):** Effect of $Sd\ stock\ return_{i,t+1}$

| | $Low\ \ \sigma(stock\ return)_{i,t+1}$ | | | $High\ \ \sigma(stock\ return)_{i,t+1}$ | | |
|---|---|---|---|---|---|---|
| Variables | (1)<br>$COD_{i,t}$ | (2)<br>$COD_{i,t}$ | (3)<br>$COD_{i,t}$ | (4)<br>$COD_{i,t}$ | (5)<br>$COD_{i,t}$ | (6)<br>$COD_{i,t}$ |
| $FBFTIS_{i,t-1}$ | -0.009** | -0.011** | -0.008* | -0.004 | -0.003 | -0.005 |
| | (-2.07) | (-2.41) | (-1.89) | (-0.84) | (-0.44) | (-1.09) |
| $Ln\ (Total\ revenue)_{i,t-1}$ | -0.388*** | -0.265*** | -0.399*** | -0.562*** | -0.417*** | -0.472*** |
| | (-4.42) | (-2.82) | (-4.31) | (-4.97) | (-3.46) | (-4.29) |
| $Tobin's\ Q_{i,t-1}$ | -0.191** | -0.240*** | -0.216** | -0.119** | -0.122** | -0.144*** |
| | (-1.97) | (-3.23) | (-2.31) | (-2.12) | (-2.27) | (-2.64) |
| $PB_{i,t-1}$ | 0.081* | 0.107** | 0.079* | 0.069* | 0.024 | 0.060 |
| | (1.87) | (2.41) | (1.84) | (1.73) | (0.58) | (1.49) |
| $Firm\ Age_{i,t-1}$ | 0.263* | 0.477*** | 0.336** | 0.377* | 0.289 | 0.364* |
| | (1.72) | (2.92) | (2.22) | (1.75) | (1.35) | (1.76) |
| $Liquid\ ratio_{i,t-1}$ | -0.227*** | -0.224*** | -0.231*** | -0.132** | -0.144*** | -0.131** |
| | (-6.23) | (-6.19) | (-6.59) | (-2.45) | (-2.67) | (-2.42) |
| $Size_{i,t-1}$ | 0.322*** | 0.204** | 0.339*** | 0.549*** | 0.360** | 0.459*** |
| | (3.71) | (2.13) | (3.68) | (4.12) | (2.52) | (3.57) |
| $CPI_{i,t-1}$ | 0.148 | 0.144 | 0.237** | 0.227* | 0.460*** | 0.139 |
| | (1.39) | (1.15) | (2.34) | (1.70) | (3.22) | (1.09) |
| $GDP\ per\ capita_{i,t-1}$ | -0.062 | -0.022 | -0.004 | 0.321*** | 0.323*** | -0.004 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (-0.95) | (-0.33) | (-0.25) | (3.74) | (3.53) | (-0.26) |
| *Constant* | -1.563 | -2.485* | -2.543* | -6.677*** | -5.727*** | -3.757** |
| | (-1.09) | (-1.91) | (-1.88) | (-3.54) | (-2.90) | (-2.34) |
| *Province FE* | YES | YES | NO | YES | YES | NO |
| *Year FE* | YES | YES | YES | YES | YES | YES |
| *Industry FE* | YES | NO | YES | YES | NO | YES |
| *Observations* | 866 | 866 | 866 | 679 | 679 | 679 |
| *R-squared* | 0.442 | 0.300 | 0.408 | 0.437 | 0.259 | 0.388 |

Note: This panel presents the results for *FBFTIS*, $\sigma(stock\ return)_{i,t+1}$ and firms' *COD*. In columns (1), (2) and (3), I conduct subsample analysis for borrowing firms with below-median value future net profit ($Low\ \sigma(stock\ return)_{i,t+1}$) in the sample. In columns (4), (5) and (6), I conduct subsample analysis for borrowing firms with above-median value of future net profit ($High\ \sigma(stock\ return)_{i,t+1}$) in the sample.

**Table 4.10 (Panel B):** Effect of $\sigma(ROA)_{i,t+1}$

| | $Low\ \sigma(ROA)_{i,t+1}$ | | | $High\ \sigma(ROA)_{i,t+1}$ | | |
|---|---|---|---|---|---|---|
| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
| | $COD_{i,t}$ | $COD_{i,t}$ | $COD_{i,t}$ | $COD_{i,t}$ | $COD_{i,t}$ | $COD_{i,t}$ |
| $FBFTIS_{i,t-1}$ | -0.011** | -0.005 | -0.011** | -0.003 | -0.009 | -0.005 |
| | (-2.32) | (-1.03) | (-2.22) | (-0.52) | (-1.51) | (-1.05) |
| $Ln\ (Total\ revenue)_{i,t-1}$ | -0.460*** | -0.349*** | -0.412*** | -0.413*** | -0.354*** | -0.405*** |
| | (-4.28) | (-2.99) | (-3.91) | (-3.20) | (-3.16) | (-3.45) |
| $Tobin's\ Q_{i,t-1}$ | -0.111** | -0.179*** | -0.115** | -0.348*** | -0.322*** | -0.370*** |
| | (-1.99) | (-3.50) | (-2.33) | (-3.19) | (-2.78) | (-3.57) |
| $PB_{i,t-1}$ | 0.065* | 0.089** | 0.053 | 0.180*** | 0.125* | 0.191*** |
| | (1.69) | (2.24) | (1.50) | (2.79) | (1.80) | (2.92) |
| $Firm\ Age_{i,t-1}$ | 0.183 | 0.280 | 0.244 | 0.345 | 0.449* | 0.416** |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (0.92) | (1.55) | (1.26) | (1.60) | (1.97) | (2.06) |
| $Liquid\ ratio_{i,t-1}$ | -0.238*** | -0.242*** | -0.224*** | -0.155** | -0.158*** | -0.159*** |
| | (-6.70) | (-6.30) | (-6.61) | (-2.51) | (-2.72) | (-2.76) |
| $Size_{i,t-1}$ | 0.371*** | 0.272** | 0.321*** | 0.373*** | 0.232* | 0.378*** |
| | (2.86) | (2.21) | (2.59) | (2.80) | (1.91) | (3.03) |
| $CPI_{i,t-1}$ | 0.288** | 0.416*** | 0.387*** | -0.045 | -0.103 | -0.015 |
| | (2.32) | (2.84) | (3.42) | (-0.32) | (-0.70) | (-0.12) |
| $GDP\ per\ capita_{i,t-1}$ | 0.054 | 0.026 | -0.001 | 0.082 | 0.092 | 0.002 |
| | (0.75) | (0.36) | (-0.08) | (1.02) | (1.12) | (0.11) |
| *Constant* | -2.054 | -2.621 | -1.956 | -3.317* | -1.495 | -3.216* |
| | (-1.10) | (-1.63) | (-1.27) | (-1.75) | (-0.85) | (-1.85) |
| *Province FE* | YES | YES | NO | YES | NO | NO |
| *Year FE* | YES | YES | YES | YES | YES | YES |
| *Industry FE* | YES | NO | YES | YES | YES | YES |
| *Observations* | 727 | 727 | 727 | 695 | 695 | 695 |
| *R-squared* | 0.425 | 0.300 | 0.396 | 0.440 | 0.255 | 0.406 |

Note: This panel presents the results for *FBFTIS*, $Sd\ ROA_{i,t+1}$ and firms' *COD*. In columns (1), (2) and (3), I conduct subsample analysis for borrowing firms with below-median value future net profit ($Low\ \sigma(ROA)_{i,t+1}$) in the sample. In columns (4), (5) and (6), I conduct subsample analysis for borrowing firms with above-median value of future net profit ($High\ \sigma(ROA)_{i,t+1}$) in the sample. All explanatory variables lag by one year. Standard errors are clustered at the firm level and reported in parentheses beneath coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

#### 4.6.2.2 Management inefficiency

Existing literature records that ineffective management can exacerbate moral hazard issues within a firm. Poor management practices can lead to inadequate internal controls, resulting in resource misallocation and waste, or encourage opportunistic behaviors where individuals prioritize short-term gains and personal benefits over long-term stability and firm growth (Engelen, 2015; Margiotta & Miller, 2000). These inefficiencies are often invisible to lending banks, which are external to the firm. Thus, banks may impose higher borrowing costs on firms to compensate for the potentially higher monitoring costs associated with poor management. However, the adoption of Fintech by banks can decrease the cost of borrowing for firms by better detecting post-lending moral hazard, particularly in terms of management inefficiency.

Therefore, I test whether the negative relationship between *FBFTIS* and *COD* is more pronounced for firms with better management efficiency. I capture management inefficiency in two dimensions. The first is the agency cost, measured by manager expense ratio (managerial expense over operation revenue). The second is the operational cost, measured by the operating expense ratio (the sum of administrative expenses and selling expenses divided by operating revenue) (Guo, Li, Wang, & Mardani, 2023). Also, to capture the concept of after-lending management efficiency, I have taken one year forward in both agency cost and operational cost.

Panel A of Table 4.11 shows that for borrowing firms with lower future agency costs, *FBFTIS* has a significantly negative association with *COD* (showing in column (4), (5), (6)). However, for firms with higher agency costs, the significance of this association disappears (see column (1), (2), (3)). This suggests that borrowing firms that make more efforts to reduce agency costs may be offered a lower cost of debt by lending banks with a higher level of Fintech adoption. Similarly, in Panel B of Table 4.11, I find some evidence that for firms with lower operational costs, *FBFTIS* may decrease *COD*. The coefficient estimates of *FBFTIS* are negative and statistically significant at the 5% to 10% level (see column (4), (5), (6)). However, for firms with higher operational costs, the significance of this association disappears when controlling for all fixed effects. Overall, these findings support the idea that when the lending banks of the firm have a higher level of Fintech development, the borrowing firm is more likely to have a lower cost of bank debt when they have better management efficiency in the future.

**Table 4. 11 (Panel A):** Effect of agency cost

| Variables | High $agent\ cost_{i,t+1}$ | | | Low $agent\ cost_{i,t+1}$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | $COD_{i,t}$ | $COD_{i,t}$ | $COD_{i,t}$ | $COD_{i,t}$ | $COD_{i,t}$ | $COD_{i,t}$ |
| $FBFTIS_{i,t-1}$ | -0.003 | -0.004 | -0.005 | -0.015*** | -0.014** | -0.013** |
| | (-0.71) | (-0.93) | (-1.30) | (-2.68) | (-2.28) | (-2.33) |
| $Ln\ (Total\ revenue)_{i,t-1}$ | -0.080 | -0.153 | -0.034 | -0.609*** | -0.493*** | -0.602*** |
| | (-0.87) | (-1.61) | (-0.35) | (-5.15) | (-3.96) | (-5.11) |
| $Tobin's\ Q_{i,t-1}$ | -0.103 | -0.149** | -0.105 | -0.116** | -0.153*** | -0.136*** |
| | (-1.53) | (-2.23) | (-1.45) | (-2.45) | (-3.22) | (-3.02) |
| $PB_{i,t-1}$ | 0.022 | 0.016 | 0.007 | 0.082** | 0.082** | 0.107*** |
| | (0.63) | (0.41) | (0.20) | (2.08) | (2.10) | (2.61) |
| $Firm\ Age_{i,t-1}$ | -0.041 | 0.029 | 0.046 | 0.535*** | 0.595*** | 0.529*** |
| | (-0.20) | (0.14) | (0.23) | (3.49) | (3.50) | (3.11) |
| $Liquid\ ratio_{i,t-1}$ | -0.214*** | -0.224*** | -0.214*** | -0.176*** | -0.183*** | -0.175*** |
| | (-5.13) | (-5.25) | (-4.40) | (-4.45) | (-4.24) | (-4.70) |
| $Size_{i,t-1}$ | 0.007 | 0.078 | -0.020 | 0.701*** | 0.494*** | 0.695*** |
| | (0.08) | (0.80) | (-0.21) | (5.01) | (3.48) | (4.80) |
| $CPI_{i,t-1}$ | -0.134 | -0.116 | -0.089 | 0.472*** | 0.457*** | 0.519*** |
| | (-1.05) | (-0.81) | (-0.82) | (3.91) | (3.50) | (4.62) |
| $GDP\ per\ capita_{i,t-1}$ | 0.072 | 0.091 | -0.022 | 0.096 | 0.094 | -0.011 |
| | (0.79) | (0.92) | (-1.29) | (1.29) | (1.33) | (-0.60) |
| *Constant* | -0.839 | -1.101 | -0.746 | -8.213*** | -6.142*** | -7.626*** |
| | (-0.53) | (-0.67) | (-0.59) | (-4.36) | (-3.22) | (-4.00) |
| *Province FE* | YES | YES | NO | YES | YES | NO |

| | | | | | | |
|---|---|---|---|---|---|---|
| *Year FE* | YES | YES | YES | YES | YES | YES |
| *Industry FE* | YES | NO | YES | YES | NO | YES |
| *Observations* | 785 | 791 | 787 | 835 | 843 | 836 |
| *R-squared* | 0.424 | 0.261 | 0.365 | 0.472 | 0.317 | 0.440 |

Note: This panel presents the results for *FBFTIS*, future *agency cost* and firms' *COD*. In columns (1), (2) and (3), I conduct subsample analysis for borrowing firms with above-median value future agency cost ($High\ agent\ cost_{i,t+1}$) in the sample. In columns (4), (5) and (6), I conduct subsample analysis for borrowing firms with below-median value of future agency cost ($Low\ agent\ cost_{i,t+1}$) in the sample.

**Table 4.11 (Panel B):** Effect of operational cost

| Variables | High $operational\ cost_{i,t+1}$ | | | Low $operational\ cost_{i,t+1}$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | $COD_{i,t}$ | $COD_{i,t}$ | $COD_{i,t}$ | $COD_{i,t}$ | $COD_{i,t}$ | $COD_{i,t}$ |
| $FBFTIS_{i,t-1}$ | -0.006 | -0.006 | -0.008** | -0.011** | -0.011** | -0.010* |
| | (-1.42) | (-1.37) | (-2.01) | (-2.16) | (-2.06) | (-1.95) |
| $Ln\ (Total\ revenue)_{i,t-1}$ | -0.159 | -0.110 | -0.078 | -0.830*** | -0.725*** | -0.829*** |
| | (-1.63) | (-1.11) | (-0.79) | (-6.63) | (-7.44) | (-6.97) |
| $Tobin's\ Q_{i,t-1}$ | -0.004 | -0.007 | -0.023 | -0.111** | -0.157*** | -0.118** |
| | (-0.04) | (-0.07) | (-0.24) | (-2.40) | (-3.49) | (-2.58) |
| $PB_{i,t-1}$ | -0.007 | -0.000 | -0.006 | 0.061* | 0.078** | 0.073* |
| | (-0.16) | (-0.01) | (-0.15) | (1.70) | (2.14) | (1.96) |
| $Firm\ Age_{i,t-1}$ | 0.056 | 0.152 | 0.140 | 0.402** | 0.533*** | 0.378** |
| | (0.27) | (0.77) | (0.69) | (2.44) | (3.05) | (2.23) |

| | | | | | | |
|---|---|---|---|---|---|---|
| $Liquid\ ratio_{i,t-1}$ | -0.230*** | -0.231*** | -0.223*** | -0.186*** | -0.185*** | -0.179*** |
| | (-5.54) | (-5.48) | (-4.61) | (-4.46) | (-4.31) | (-4.74) |
| $Size_{i,t-1}$ | 0.069 | 0.043 | -0.015 | 0.880*** | 0.672*** | 0.890*** |
| | (0.74) | (0.43) | (-0.16) | (5.95) | (5.65) | (6.14) |
| $CPI_{i,t-1}$ | -0.144 | -0.101 | -0.046 | 0.358*** | 0.424*** | 0.393*** |
| | (-1.07) | (-0.70) | (-0.39) | (3.09) | (3.51) | (3.47) |
| $GDP\ per\ capita_{i,t-1}$ | 0.094 | 0.159 | -0.004 | 0.060 | 0.052 | -0.020 |
| | (1.00) | (1.55) | (-0.22) | (0.84) | (0.78) | (-1.08) |
| *Constant* | -0.864 | -2.284 | -0.369 | -6.573*** | -4.655*** | -6.299*** |
| | (-0.53) | (-1.40) | (-0.27) | (-3.66) | (-2.69) | (-3.56) |
| *Province FE* | YES | YES | NO | YES | YES | NO |
| *Year FE* | YES | YES | YES | YES | YES | YES |
| *Industry FE* | YES | NO | YES | YES | NO | YES |
| *Observations* | 762 | 770 | 764 | 841 | 848 | 842 |
| *R-squared* | 0.409 | 0.259 | 0.352 | 0.468 | 0.332 | 0.429 |

Note: This panel presents the results for *FBFTIS*, future operational cost and firms' *COD*. In columns (1), (2) and (3), I conduct subsample analysis for borrowing firms with above-median value future operational cost (*High* $operational\ cost_{i,t+1}$) in the sample. In columns (4), (5) and (6), I conduct subsample analysis for borrowing firms with below-median value of future operational cost (*Low* $operational\ cost_{i,t+1}$) in the sample. All explanatory variables lag by one year. Standard errors are clustered at the firm level and reported in parentheses beneath coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Accordingly, reducing moral hazard is another plausible channel through which the adoption of Fintech by lending banks lowers the cost of bank debt for borrowing firms. This effect is particularly pronounced for firms with better risk controls and management efficiency after lending.

### 4.6.3. Alternative explanation: Weighted bank operating cost

In this section, I test an alternative explanation which explores whether the negative relationship between banks' Fintech development and firms' cost of debt is due to the optimization of banks' operational process which reduces the overall bank operating costs. As documented in the extant literature, the digitalization and automation of the business process can eliminate waste, maximize the system capacities, optimize the expenditures and resources (Bu, Jeong, & Koh, 2022; Sungau & Ndunguru, 2015). In this logic, the overall operating costs of lending banks may be reduced by the adoption of Fintech, thereby potentially reducing the cost of bank debt for borrowing firms. To investigate whether this channel exists, I construct the following model:

$$\begin{aligned} COD_{i,t} = \pi_0 &+ \pi_1 FBFTIS_{i,t-1} * WBOC_{i,t-1} + \pi_2 FBFTIS_{i,t-1} + \pi_3 WBOC_{i,t-1} \\ &+ \sum X_{i,t-1} + \sum PROVMacro_{i,t-1} + YearFE + IndustryFE \\ &+ ProvinceFE + \tau_{i,t} \end{aligned}$$

[5]

Where $WBOC$ is the weighted bank operating cost which is calculated by $Weight_{i,b,t}$ * $Bank\ operating\ cost_{b,t}$. $Weight_{\mathrm{i,b,t}}$ refers to the ratio of the loan amount borrowed by firm$_i$ from the lending $bank_b$ to the total loan amount borrowed by firm i from all banks in year$_t$.

Table 4.12 presents the results of the regression. I include all control variables in the three columns. Column (1) controls for $Year, Industry\ and\ Province$ fixed effect, while column (2) controls for $Year$ and $Province$ fixed effect and column (3) controls for $Year$ and $Industry$ fixed effect. The coefficient of the interaction term ($\pi_1$) examines how the relationship between $FBFTIS$ and firms' $COD$ is affected by the bank's operational costs.

In all columns, the coefficients of the interaction terms are significantly negative at the 1% to 5% level, suggesting that higher operational costs amplify the negative relationship between lending banks' Fintech development and borrowing firms' cost of debt. Specifically, for each unit increase in the interaction between $FBFTIS$ and $WBOC$, the $COD$ decreases by 0.023, 0.015, and 0.013 in column (1), (2), and (3), respectively. The results suggest that this inferred channel is questionable and could be the opposite. The adoption of Fintech technologies can lead to higher operational costs for banks, including the costs of implementing new technologies, training staff, and maintaining these systems. These costs are not transferred from the lending banks to the borrowing firms, the borrowing costs of firms may still decrease.

**Table 4. 12:** effect of weighted bank operating cost

| Variables | (1)<br>$COD_{i,t}$ | (2)<br>$COD_{i,t}$ | (3)<br>$COD_{i,t}$ |
|---|---|---|---|
| $FBFTIS_{i,t-1} * WBOC_{i,t-1}$ | -0.014*** | -0.015*** | -0.013** |
| | (-2.68) | (-2.62) | (-2.45) |
| $FBFTIS_{,t-1}$ | -0.009*** | -0.010*** | -0.009*** |
| | (-3.34) | (-3.25) | (-3.13) |
| $WBOC_{i,t-1}$ | 0.040** | 0.037* | 0.036* |
| | (2.15) | (1.65) | (1.89) |
| $Ln\ (Total\ revenue)_{i,t-1}$ | -0.341*** | -0.285*** | -0.327*** |
| | (-5.34) | (-4.30) | (-5.19) |
| $Tobin's\ Q_{i,t-1}$ | -0.106*** | -0.144*** | -0.116*** |
| | (-3.30) | (-4.32) | (-3.74) |
| $PB_{i,t-1}$ | 0.040** | 0.053** | 0.045** |
| | (2.00) | (2.40) | (2.19) |
| $Firm\ Age_{i,t-1}$ | 0.227* | 0.308** | 0.244** |
| | (1.96) | (2.44) | (2.02) |
| $Liquid\ ratio_{i,t-1}$ | -0.182*** | -0.181*** | -0.180*** |
| | (-6.68) | (-6.85) | (-6.74) |
| $Size_{i,t-1}$ | 0.287*** | 0.235*** | 0.277*** |

| | | | |
|---|---|---|---|
| | (4.15) | (3.26) | (4.07) |
| $CPI_{i,t-1}$ | 0.146** | 0.174** | 0.180*** |
| | (2.16) | (2.35) | (2.73) |
| $GDP\ per\ capita_{i,t-1}$ | 0.078** | 0.080** | -0.013 |
| | (2.04) | (2.00) | (-1.40) |
| *Constant* | -3.079*** | -3.403*** | -2.516*** |
| | (-3.25) | (-3.69) | (-2.88) |
| *Province FE* | YES | YES | NO |
| *Year FE* | YES | YES | YES |
| *Industry FE* | YES | NO | YES |
| *Observations* | 2,159 | 2,159 | 2,159 |
| *R-squared* | 0.417 | 0.320 | 0.396 |

Note: This table presents the results for *FBFTIS*, *WBOC* and firms' *COD*. Column 1 includes Year, Industry, and Province fixed effects, as well as all control variables. Columns 2 and 3 explore variations in fixed effects, with Column 2 including Province and Year fixed effects, and Column 3 including Industry and Year fixed effects. All explanatory variables lag by one year. Standard errors are clustered at the firm level and reported in parentheses beneath coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

### 4.6.4. Other analyses: Fixed assets

In this section, I conduct an additional analysis to explore whether the negative relationship between banks' Fintech development and firms' cost of debt is more pronounced for firms with fewer fixed assets. The level of fixed assets owned by a borrowing firm can significantly influence its cost of debt for two primary reasons. First, the amount of fixed assets indicates the firm's ability to offer collateral, which is a key factor in securing loans at favorable terms. Second, firms with lower levels of fixed assets may face collateral requirements that negatively impact their profitability, liquidity, solvency, and overall ability to repay loans. This is because collateral requirements can restrict the use of pledged assets, potentially leading to a shortage of operating assets (Biguri & Stahl, 2024). Therefore, I examine whether the negative relationship between banks' Fintech development and the cost of debt depends on the level of fixed assets. Specifically, I investigate whether banks' adoption of Fintech can help mitigate the disadvantages faced by firms with lower levels of fixed assets, potentially offsetting the negative impacts of collateral requirements.

To test this, I use $FIXED$ to indicate the level of fixed assets of borrowing firms, measured by ratio of Fixed asset (the ratio between the net value of fixed asset and total asset). I add $FIXED$ into the baseline regression as an interaction term and estimate the regression below:

$$COD_{i,t} = \theta_0 + \theta_1 FBFTIS_{i,t-1} * FIXED_{i,t-1} + \theta_2 FBFTIS_{i,t-1} + \theta_3 FIXED_{i,t-1} + \sum X_{i,t-1} + \sum PROVMacro_{i,t-1} + YearFE + IndustryFE + ProvinceFE + \vartheta_{i,t}$$

[6]

The $FIXED$ lag for one period as are other variables on the right side. The coefficient of the interaction term ($\theta_1$) captures how the relationship between $FBFTIS$ and firms' $COD$ varies across the level of fixed assets of firms. As shown in Table 4.13, I include all control variables in the three columns. Column (1) controls for $Year, Industry\ and\ Province$ fixed effect, while column (2) controls for $Year$ and $Province$ fixed effect and column (3) controls for $Year$ and $Industry$ fixed effect.

**Table 4. 13:** The effect of fixed assets

| Variables | (1)<br>$COD_{i,t}$ | (2)<br>$COD_{i,t}$ | (3)<br>$COD_{i,t}$ |
|---|---|---|---|
| $FBFTIS_{i,t-1} * FIXED_{i,t-1}$ | -0.034** | -0.044*** | -0.041*** |
| | (-2.20) | (-2.71) | (-2.59) |
| $FBFTIS_{i,t-1}$ | 0.001 | 0.003 | 0.003 |
| | (0.32) | (0.64) | (0.66) |
| $FIXED_{i,t-1}$ | 1.240*** | 1.811*** | 1.182*** |
| | (3.47) | (5.35) | (3.34) |
| $Ln\ (Total\ revenue)_{i,t-1}$ | -0.339*** | -0.293*** | -0.328*** |
| | (-5.25) | (-4.50) | (-5.14) |
| $Tobin's\ Q_{i,t-1}$ | -0.111*** | -0.150*** | -0.119*** |

| | | | |
|---|---|---|---|
| | (-3.51) | (-4.64) | (-3.88) |
| $PB_{i,t-1}$ | 0.044** | 0.060*** | 0.048** |
| | (2.21) | (2.79) | (2.36) |
| $Firm\ Age_{i,t-1}$ | 0.218* | 0.315** | 0.235* |
| | (1.86) | (2.50) | (1.91) |
| $Liquid\ ratio_{i,t-1}$ | -0.170*** | -0.160*** | -0.169*** |
| | (-6.24) | (-6.24) | (-6.33) |
| $Size_{i,t-1}$ | 0.274*** | 0.229*** | 0.269*** |
| | (3.98) | (3.28) | (3.96) |
| $CPI_{i,t-1}$ | 0.149** | 0.176** | 0.179*** |
| | (2.24) | (2.46) | (2.75) |
| $GDP\ per\ capita_{i,t-1}$ | 0.073* | 0.072* | -0.011 |
| | (1.88) | (1.80) | (-1.18) |
| *Constant* | -3.088*** | -3.498*** | -2.604*** |
| | (-3.27) | (-3.84) | (-3.00) |
| *Province FE* | YES | YES | NO |
| *Year FE* | YES | YES | YES |
| *Industry FE* | YES | NO | YES |
| *Observations* | 2,159 | 2,159 | 2,159 |
| *R-squared* | 0.420 | 0.337 | 0.400 |

This table presents the results for *FBFTIS*, *FIXED* and firms' *COD*. Column 1 includes *Year, Industry,* and *Province* fixed effects, as well as all control variables. Columns 2 and 3 explore variations in fixed effects, with Column 2 including *Province* and *Year* fixed effects, and Column 3 including *Industry* and *Year* fixed effects. All explanatory variables lag by one year. Standard errors are clustered at the firm level and reported in parentheses beneath coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

The coefficients of the interaction term between $FBFTIS$ and $FIXED$ are significantly negative in all columns. The results illustrate that lending banks' Fintech development has a more persistent negative impact on high fixed asset borrowing firms' $COD$ while the lower number of fixed assets can be still unfavorable.

## 4.7. Conclusion

This research offers compelling empirical evidence on the significant role that banks' Fintech adoption plays in reducing firms' cost of debt. By examining the mechanisms through which Fintech affects the cost of bank debt, the study explores how technology can transform traditional banking practices, ultimately benefiting firms and supporting the real economy.

The findings reveal that Fintech adoption by banks generally leads to a reduction in borrowing costs for firms. This is primarily achieved through the mitigation of information asymmetries between lenders and borrowers, reducing costs related to adverse selection and moral hazard. I also find that although the Fintech adoption can lead to higher operational costs for banks, including implementing new technologies, training staff, and maintaining systems, these costs are not transferred to borrowing firms. The robustness of the findings is reinforced through the use of two-stage least squares regression and difference-in-differences analyses. These methods help address concerns related to endogeneity, enhancing the validity and reliability of the results.

Overall, this research contributes to the broader understanding of how technological advancements in the banking sector can support the real economy. By demonstrating the tangible benefits of Fintech adoption, this study highlights the importance of integrating advanced technologies into traditional banking practices to enhance financial services. As the financial landscape continues to evolve, such integration could serve as a catalyst for innovation, helping to maintain competitiveness and resilience in a rapidly changing economic environment.

# Chapter 5
# General Conclusion

As the financial landscape transforms under the influence of Fintech and shadow banking activities, the traditional roles and operations of banks are destabilized. Understanding these unprecedented challenges and opportunities is what motivates this study. This thesis responds to the pressing need to explore how the interplay between banks' shadow activities and Fintech adoption reshapes risk management practices and strategic behaviors. By examining these dynamics, the research highlights critical implications for the stability and efficiency of financial markets. It emphasizes the necessity for banks to adapt to a rapidly evolving environment characterized by innovative technologies and alternative financial systems. Understanding these questions not only contributes to academic discourse but also provides valuable insights for industry practitioners and policymakers. Importantly, this thesis uncovers the impacts of banks' shadow activities and Fintech adoption, as well as their implications for bank risk and cost of debt for borrowing firms. In the subsequent section, I will summarize the major findings, outline the contributions made to the existing body of knowledge.

This thesis uncovers critical findings into the impacts of banks' shadow activities and Fintech adoption, as well as their implications for bank risk management and cost of debt of borrowing firms. Chapter 2 reveals that while engaging in shadow activities can initially reduce banks' realized risks, this effect is significantly influenced by the complexity of their business and organizational structures. Specifically, banks characterized by complexities will find that shadow activities can increase their exposure to risk, highlighting the intricate balance between shadow banking practices and business complexity.

Building on this foundation, Chapter 3 explores the interplay between Fintech and banks' shadow activities. It finds that banks implementing Fintech solutions tend to realize lower risk, showcasing the potential of technology to stabilize operations. However, Fintech may also intensify banks' engagement in shadow activities, especially within investment-focused banks, which could weaken the risk-reducing effect. This nuanced relationship emphasizes the dual role of Fintech as both a stabilizer and a catalyst for increased shadow activity risks.

Chapter 4 further examines the impact of Fintech adoption by lending banks on reducing borrowers' debt costs. This cost reduction effect is largely attributed to the minimization of information asymmetries, which allows borrowing firms, particularly those with financial constraints, to benefit from more favorable credit conditions. The study employs robust methodologies to address concerns of endogeneity, affirming the reliability of these insights. Moreover, it identifies reduced adverse selection and decreased moral hazard as key mechanisms through which Fintech drives down borrowing costs. This finding underscores Fintech's transformative impact on traditional bank-firm relationships by enhancing risk management and lending efficiency.

This thesis significantly enriches the existing body of literature by providing insights into the interplay between banks' shadow activities, risk management strategies, and the role of Fintech in the evolving banking landscape. First, it addresses the critical issue of banks' shadow activities, offering a comprehensive analysis of how traditional banks engage in shadow banking practices and the implications for risk management. By examining the impact of these practices on bank complexity and the associated risks, this research fills a vital gap in understanding how banks navigate the complexities introduced by non-bank financial institutions. The findings reveal that the strategies employed by banks in the realm of shadow banking not only affect their risk profiles but also raise important questions regarding regulatory adequacy and financial stability.

Second, the exploration of the relationship between banks' shadow activities and Fintech adoption further extends this discourse. Chapter 3 investigates how the intersection of these dynamics influences risk management and operational strategies within traditional banks. By highlighting how Fintech can serve as both a tool for mitigating risks and a catalyst for enhancing banks' approaches to shadow activities, this research provides valuable insights into the dual role of technology in modern finance. Lastly, Chapter 4 focuses specifically on Fintech's impact on borrowing costs, contributing to the literature by elucidating how technological advancements in financial services can promote efficiency and reduce information asymmetry. This research advances the understanding of the mechanisms through which Fintech adoption influences loan pricing, ultimately revealing how banks can leverage technology to support economic growth and relieve financial burdens on firms.

There are several limitations stemming from research design which may lead to how future research can be developed further. First, in Chapter 2, I have utilized a range of bank-level control variables, including ln (total assets), net loans to total assets, cost to income, equity to assets, and ROA. However, they could potentially lead to endogeneity. For instance, ROA can be influenced by various factors such as firm leverage, firm size, and board size, all of which may be correlated with the error term in the model. To balance the need to include these variables and the endogeneity issues they induce, further research could consider using instrumental variables and employ a two-stage least square (2SLS) approach.

Second, in Chapter 3, the study utilizes "Fintech 3.0" as a proxy measure and treatment variable, employing a staggered Difference-in-Differences (DIDs) approach to assess its impact. One significant limitation of this methodology is the potential for self-selection bias. Banks that adopt Fintech solutions might differ systematically from those that do not, leading to differences in underlying characteristics that could influence the results. This bias can obscure the true effects of Fintech adoption on bank performance and risk management, as the comparability between treated and control groups may not be fully established. Further research could consider additional controls or alternative methodologies, such as propensity score matching, to better account for these differences and strengthen causal inferences.  Also, there is an issue of reverse causality between Fintech and bank risk. The Fintech adoption of banks is potentially not random. For instance, banks with higher risk profiles may face increased regulatory scrutiny, which can affect their willingness to adopt Fintech solutions. While I have employed a propensity score matching approach to absorb some of the firm-specific features, more rigorous treatment may be necessary, such as identifying instrumental variables.

Third, in Chapter 4, the use of text mining techniques to analyze banks' annual reports and develop a bank-level Fintech development index presents its own set of limitations. Annual reports often contain restricted disclosures, which may not fully represent the true extent of a bank’s Fintech activities. Additionally, they can be polished or "dressed up" to present a more favorable image, potentially leading to an incomplete or biased understanding of a bank's Fintech integration. The methodologies employed, including word vector representations (Word2Vec) and Term Frequency-Inverse Document Frequency (TF-IDF) for indexing, have inherent limitations regarding semantic understanding and context capture. For instance, these techniques may not sufficiently account for the nuances of language used in financial reporting, potentially affecting the accuracy of the Fintech development index. Future research could explore more advanced natural language processing techniques or incorporate qualitative analyses to enhance the richness and reliability of the index.

In addition to research design challenges, this thesis is also constrained by limitations related to data availability. For example, the dataset primarily focuses on publicly listed banks, excluding smaller and medium-sized banks that may operate under different conditions or engage differently in shadow activities and Fintech initiatives. This exclusion can introduce bias and limit the applicability of the findings to the broader banking sector, as these smaller institutions might exhibit different risk profiles or strategic behaviors.

Furthermore, while the sample used in the study is global, a significant limitation arises from the variability in disclosure practices across different countries. In many jurisdictions, certain aspects of financial disclosure, especially regarding Fintech adoption and shadow banking activities, are not mandatory. This results in inconsistent and potentially incomplete datasets, as detailed information is often lacking or selectively reported. Consequently, the cross-country comparisons and insights drawn from the analysis may be affected, as variations in regulatory environments and disclosure norms can influence the quality and depth of the data.

Overall, by acknowledging these limitations, this thesis establishes a foundation for future studies that aim to refine methodologies and expand the scope of investigation into the intricate relationships among banks' shadow activities and Fintech adoption.

Looking forward, future research on banks' shadow activities and Fintech adoption presents numerous opportunities to expand knowledge in this dynamic area. Potential insights can be sorted into the following aspects:

First, it is important to present more empirical evidence regarding the role of banks' shadow activities in the real economy. Further exploration is warranted to address how banks' shadow activities influence a wide range of dynamics among borrowing firms, including factors such as environmental, social, and governance (ESG) considerations, firm size, geographical location, and innovation capabilities. Understanding these relationships can help clarify the broader economic impact of shadow banking practices and inform policymakers about the potential benefits and drawbacks associated with these activities.

Second, while previous research and this thesis have begun integrating Fintech with operational research and risk management, there is a need to further investigate how Fintech reshapes the financial sector in areas such as customer service and retention marketing. This includes examining recent advancements in Fintech, such as generative AI technologies (e.g., GPT models), which have the potential to enhance customer interactions and streamline marketing efforts. Exploring these applications can provide deeper insights into how financial institutions can leverage technology to improve service delivery and maintain competitive advantages in a rapidly evolving market.

Third, while this thesis has begun to explore the interplay between Fintech adoption and the shadow banking system, future research should delve deeper into the complexities of this relationship. Specifically, it will be essential to examine how emerging Fintech innovations further transform shadow banking practices beyond the scope of this study. Areas for deeper exploration could include the implications of data analytics and machine learning on risk assessment in shadow banking, how decentralized finance (DeFi) models challenge traditional shadow banking frameworks, and the potential regulatory responses to these changes. Such in-depth examinations can provide a more comprehensive understanding of the evolving landscape and its implications for financial stability and regulatory governance.

By pursuing these avenues, future research can further clarify the influence of banks' shadow activities and examine the transformative role of Fintech in reshaping the traditional banking industry. These insights will provide valuable guidance for the future development of traditional banking by outlining pathways for adaptation and growth in a rapidly evolving financial landscape. Ultimately, this branch of research will be essential for crafting effective regulatory policies that ensure financial stability while fostering innovation and resilience within the banking ecosystem.

# Appendix:

## Appendix A1 (Chapter 2):

Full list of NACE Code (main section)

| NACE Code | Economic Area |
|---|---|
| A | Agriculture, Forestry and Fishing |
| B | Mining and Quarrying |
| C | Manufacturing |
| D | Electricity, Gas, Steam and Air Conditioning Supply |
| E | Water Supply; Sewerage, Waste Management and Remediation Activities |
| F | Construction |
| G | Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles |
| H | Transportation and Storage |
| I | Accommodation and Food Service Activities |
| J | Information and Communication |
| K | Financial and Insurance Activities |
| L | Real Estate Activities |
| M | Professional, Scientific and Technical Activities |
| N | Administrative and Support Service Activities |
| O | Public Administration and Defense; Compulsory Social Security |
| P | Education |
| Q | Human Health and Social Work Activities |
| R | Arts, Entertainment and Recreation |
| S | Other Service Activities |
| T | Activities of Households as Employers; Undifferentiated Goods and Services Producing Activities of Households for Own Use |
| U | Activities of Extraterritorial Organizations and Bodies |

# Appendix A2 (Chapter 2):

Full list of NACE Code (4-digits)

| NACE Code (4-digits) | Economic Area |
|---|---|
| **64.1.1** | Central banking |
| **64.1.9** | Other monetary intermediation |
| **64.2.0** | Activities of holding companies |
| **64.3.0** | Trusts, funds and similar financial entities |
| **64.9.1** | Financial leasing |
| **64.9.2** | Other credit granting |
| **64.9.9** | Other financial service activities, except insurance and pension funding n.e.c. |
| **65.1.1** | Life insurance |
| **65.1.2** | Non-life insurance |
| **65.2.0** | Reinsurance |
| **65.3.0** | Pension funding |
| **66.1.1** | - Administration of financial markets |
| **66.1.2** | - Security and commodity contracts brokerage |
| **66.1.9** | Other activities auxiliary to financial services, except insurance and pension funding |
| **66.2.1** | Risk and damage evaluation |
| **66.2.2** | Activities of insurance agents and brokers |
| **66.2.9** | Other activities auxiliary to insurance and pension funding |
| **66.3.0** | Fund management activities |

# Appendix A3 (Chapter 2):

Definition of Variables:

| Type of variables | Variables | Measurement |
|---|---|---|
| Independent variables | Off balance sheet item ratio (OBS) | Off-balance sheet items/ total on and off-balance sheet exposures |
| Complexity variables | Non-interest income ratio | Non-interest income/ the sum of net interest income and non-interest income |
| | NIS/NIM | Net interest spread rate/Net interest margin |
| | Num of employees | Number of employees |
| | Num of branches | Number of branches |
| | M&A | Number of Merger and Acquiring events |
| Dependent variables | Impaired loans to equity ratio | Impaired loans/total equity |
| | ln(NPL) | Natural logarithm of non-performance loan |
| Other bank-level control variables | ln(Total asset) | Natural logarithm of total asset |
| | Net loans to total assets ratio | Net loans/total asset |
| | Cost to income ratio | Operating expense/Operating income |
| | Equity to assets ratio | Equity/asset |
| | ROA | Bank profitability |
| Macro control variables | GDP | Real GDP growth rate |
| | CPI | Core CPI growth rate |

# Appendix A4 (Chapter 2)

For the high $R^2$ values observed in the first empirical chapter, I propose several explanations. First, the inclusion of fixed effects, whether individual or time fixed effects, can lead to inflated $R^2$ values. In panel data regressions, it is common practice to employ fixed effects to control for time-invariant characteristics across banks or to account for year-specific shocks, such as macroeconomic conditions or regulatory changes, that are not captured by the control variables. Consequently, models incorporating fixed effects tend to explain a substantial portion of the variance in the dependent variable, resulting in a high level of fitness, which is reflected in high $R^2$ values. To test this, I re-estimated the baseline model by removing the fixed effects. The table in the end of the letter presents the result. It is evident that the $R^2$ values decreased from 0.918 to 0.6876 when the dependent variable is ln(NPL) and from 0.713 to 0.0902 when the dependent variable is impaired loans to equity. These results show that fixed effects significantly increase the $R^2$.

**Baseline regression without fixed effects:**

| VARIABLES | (1)<br>$\ln(NPL)_{i,t}$ | (2)<br>$Impaired\ loan\ to\ equity_{i,t}$ |
|---|---|---|
| $OBS_{i,t-1}$ | -0.159 | -29.644*** |
| | (-0.53) | (-2.84) |
| $\ln(total\ assets)_{i,t-1}$ | 1.041*** | 1.292 |
| | (31.25) | (1.15) |
| $Net\ loans\ to\ total\ asset_{i,t-1}$ | 0.013*** | 0.193** |
| | (3.75) | (1.98) |
| $Cost\ to\ income_{i,t-1}$ | -0.008** | 0.082 |
| | (-2.42) | (0.84) |
| $Equity\ to\ assets_{i,t-1}$ | 0.008 | -0.489 |
| | (0.44) | (-1.39) |
| $ROA_{i,t-1}$ | -0.190*** | -5.623*** |
| | (-4.20) | (-2.98) |
| $GDP_{i,t-1}$ | -0.020** | -0.824*** |
| | (-2.25) | (-2.71) |
| $CPI_{i,t-1}$ | 0.054*** | 0.707** |
| | (4.12) | (2.23) |
| $Constant$ | -5.431*** | 2.056 |
| | (-6.72) | (0.08) |

| | | |
|---|---|---|
| *Company FE* | NO | NO |
| *Year FE* | NO | NO |
| *Observations* | 4,079 | 4,113 |
| *R-squared* | 0.688 | 0.090 |

Note: Note: This table presents estimates from a baseline regression model [1] removing fixed effects. The dependent variable is bank risk, measured by *ln(NPL)* and *Impaired loans to equity*. The primary variable of interest is banks' shadow activities, measured by the off-balance sheet item ratio (*OBS*). Column 1 uses *ln(NPL)* as the dependent variable. Column 2 uses *Impaired loans to equity* as the dependent variable. All explanatory variables lag by one year. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Second, if both the dependent and independent variables exhibit persistence, the model is likely to fit well, resulting in high $R^2$ values. Persistence suggests that the values of variables are influenced by past values over time; therefore, the observed relationship may be largely driven by a shared time trend (past Y) rather than by X causing Y. In my paper, I have incorporated lagged explanatory variables in the regression, which helps to mitigate this concern to some extent. By using lagged X, I aim to test whether past values of X can predict current values of Y, independent of the information provided by past Y. To further address this issue, I plan to employ additional methods in the future, such as testing unit roots or utilizing dynamic panel models (GMMs).

Third, high $R^2$ values may also arise from multicollinearity among the explanatory variables. In response to this concern, I have included a correlation matrix (Page 46) to identify any strong correlations between the variables. The results indicate that while most of the correlation coefficients are significant, they are all below 0.5, suggesting that the strength of these correlations is not particularly high. This finding helps to alleviate potential concerns related to multicollinearity.

Furthermore, I conduct a forward stepwise linear regression to identify the control variables that significantly contribute to the high $R^2$ values. The table at the end of this letter details the changes in $R^2$ throughout the stepwise regression process. In Panel A, when the dependent variable is ln(NPL), ln(total assets) is the variable that contributes most significantly to thed $R^2$ value (0.6509). In Panel B, when the dependent variable is impaired loans to equity, ROA emerges as the variable that contributes most significantly to the $R^2$ value (0.0271).

## Stepwise regression:

**Panel A:** ln(NPL)

| Variable | F-value | Pr>F | $R^2$ | Change in $R^2$ |
|---|---|---|---|---|
| Off Balance sheet item ratio | 18.82 | 0.000 | 0.0046 | |
| ln(total assets) | 7701.61 | 0.004 | 0.6555 | 0.6509 |
| Net loans to total assets | 121.05 | 0.000 | 0.6654 | 0.0099 |
| Cost to income | 9.67 | 0.000 | 0.6662 | 0.0008 |
| Equity to assets | 10.77 | 0.002 | 0.6671 | 0.0009 |
| ROA | 120.43 | 0.000 | 0.6767 | 0.0096 |
| Real GDP | 13.86 | 0.000 | 0.6778 | 0.0011 |
| Core CPI | 127.52 | 0.000 | 0.6876 | 0.0098 |

Note: This table contains the results of stepwise regression analysis with the ln(NPL) as the dependent variable.

**Panel B**: Impaired loans to equity

| Variable | F-value | Pr>F | $R^2$ | Change in $R^2$ |
|---|---|---|---|---|
| Off Balance sheet item ratio | 41.69 | 0.000 | 0.0100 | |
| ln(total assets) | 24.23 | 0.000 | 0.0158 | 0.0058 |
| Net loans to total assets | 42.60 | 0.000 | 0.0259 | 0.0101 |
| Cost to income | 52.90 | 0.000 | 0.0383 | 0.0124 |
| Equity to assets | 65.15 | 0.000 | 0.0533 | 0.0150 |
| ROA | 121.15 | 0.000 | 0.0805 | 0.0271 |
| Real GDP | 23.51 | 0.000 | 0.0857 | 0.0052 |
| Core CPI | 20.31 | 0.000 | 0.0902 | 0.0045 |

Note: This table contains the results of stepwise regression analysis with the Impaired loans to equity as the dependent variable.

## Appendix B1 (Chapter 3):

Definition of variables.

| Type of variables | Variables | Measurement |
|---|---|---|
| Independent variables | Fintech | A dummy variable is set to 1 if the selected keywords appear in the banks' annual reports; otherwise, it is set to 0. |
| Banks' shadow activities variable | Off balance sheet item ratio (OBS) | Off-balance sheet items/ total on and off-balance sheet exposures |
| Dependent variables | Impaired loans to equity ratio | Impaired loans/total equity |
| | Non-Perf Loan ratio | Non-performance loan/total loans |
| | loan loss provision ratio | Loan loss provision/total loans |
| Other bank-level control variables | ln(Total asset) | Natural logarithm of total asset |
| | Net loans to total assets ratio | Net loans/total asset |
| | Cost to income ratio | Operating expense/Operating income |
| | Equity to assets ratio | Equity/asset |
| | ROA | Bank profitability |
| Macro control variables | GDP | Real GDP growth rate |
| | CPI | Core CPI growth rate |

# Appendix C1 (Chapter 4):

Definition of variables.

| Type of variable | Variable name | Measure |
|---|---|---|
| Independent variable | Firm-bank Fintech influence sore (FBFTIS) | Summing up the product of the loan weight $\text{Weight}_{i,b,t}$ and the fintech adoption score $Fintech_{TF_{IDF}t,b}$ for each bank $b$ that lends to the firm $i$ |
| Firm-level control variables | Total revenue | Natural logarithm of total revenue |
| | Tobin's Q | Market value of firm / Replacement cost of firm's assets |
| | **Price-to-Book Ratio (**PB) | Market price per share / Book value per share |
| | Firm Age | Number of years since the firm's founding |
| | Liquid ratio | Current assets / Current liabilities |
| | Size | Natural logarithm of total asset |
| Macro-economic controls | CPI | CPI index value |
| | GDP per capita | Average GDP per person |

## Appendix C2 (Chapter 4):

| Categories | Key terms (Partial) |
|---|---|
| **Internet** | Internet Technology, Internet Thinking, Internet Action, Internet Business, Internet Mobility, Internet Applications, Internet Marketing, Internet Strategy, Internet Platform, Internet Model, Internet Business Model, Internet Ecosystem, E-commerce, Electronic Commerce, Internet Plus, Online and Offline, Online to Offline, Online and Offline; |
| **Digital** | AI Customer Service, Smart Home, Robo-Advisor, Smart Tourism, Smart Environmental Protection, Smart Grid, Smart Marketing, Digital Marketing, Unmanned Retail, Internet Finance, Digital Finance, Fintech, Financial Technology, Quantitative Finance, Open Banking, Data Management, Data Mining, Data Network, Data Platform, Data Center, Data Science, Digital Control, Digital Technology, Digital Communication, Digital Network, Digital Intelligence, Digital Terminal, Digitalization, Big Data; |
| **Information** | Information System, Information Network, Information Terminal, Information Center, Informatization, Networked Information Sharing, Networking, Industrial Information, Industrial Communication, Cloud Ecosystem, Cloud Services, Cloud Platform, Cloud Computing, Stream Computing, Graph Computing, In-Memory Computing, Multi-Party Secure Computation, Neuromorphic Computing, Green Computing; |
| **Intelligence** | Smart Logistics, Smart Manufacturing, Smart Warehousing, Smart Technology, Smart Devices, Smart Production, Intelligent Connectivity, Smart Systems, Intelligence, Automatic Control, Automatic Monitoring, Automatic Surveillance, Automatic Testing, Automatic Production, Numerical Control, Integration, Integration, Integrated Solutions, Integrated Control, Integrated Systems, Industrial Cloud, Factory of the Future, Smart Fault Diagnosis, Lifecycle Management, Manufacturing Execution System, Virtualization, Virtual Manufacturing |

## Appendix C3 (Chapter 4)

In this section, I address potential endogeneity problems arising from technological capacity as a confounding factor. A firm's technological capacity may be simultaneously correlated with both fintech adoption and the cost of bank debt for borrowing firms, leading to omitted variable bias that could confound the results. To control for this source of endogeneity, I introduce additional firm-specific control variables that measure technological capacity using two proxies: (1) $Patent_{i,t-1}$, the number of patents granted, and (2) $CaRexpr_{i,t-1}$, the ratio of capitalized research expenses to net profit.

Panel A of the table presents the estimated results using $Patent_{i,t-1}$ as the measure of technological capacity, while Panel B displays the results using $CaRexpr_{i,t-1}$ as the alternative measure. Consistent with the findings from the baseline regression, the adoption of fintech by lending banks continues to show a significant negative relationship with the cost of bank debt for borrowing firms. The estimated coefficients range from -0.005 to -0.007, indicating that increased fintech adoption is associated with a reduction in the cost of bank debt.

**Panel A:**

| VARIABLES | (1)<br>$COD_{i,t}$ | (2)<br>$COD_{i,t}$ | (3)<br>$COD_{i,t}$ |
|---|---|---|---|
| $FBFTIS_{i,t-1}$ | -0.006** | -0.007** | -0.005** |
| | (-2.18) | (-2.31) | (-2.14) |
| $Ln\ (Total\ revenue)_{i,t-1}$ | -0.341*** | -0.283*** | -0.326*** |
| | (-5.33) | (-4.29) | (-5.16) |
| $Tobin's\ Q_{i,t-1}$ | -0.108*** | -0.148*** | -0.118*** |
| | (-3.42) | (-4.45) | (-3.85) |
| $PB_{i,t-1}$ | 0.043** | 0.057*** | 0.048** |
| | (2.16) | (2.60) | (2.35) |
| $Firm\ Age_{i,t-1}$ | 0.232** | 0.315** | 0.246** |
| | (2.00) | (2.50) | (2.04) |
| $Liquid\ ratio_{i,t-1}$ | -0.181*** | -0.179*** | -0.178*** |
| | (-6.63) | (-6.79) | (-6.68) |
| $Size_{i,t-1}$ | 0.292*** | 0.238*** | 0.282*** |

| | | | |
|---|---|---|---|
| | (4.20) | (3.26) | (4.14) |
| $Patent_{i,t-1}$ | -0.004*** | -0.005*** | -0.004*** |
| | (-3.34) | (-3.69) | (-3.84) |
| $CPI_{i,t-1}$ | 0.143** | 0.169** | 0.176*** |
| | (2.11) | (2.28) | (2.67) |
| $GDP\ per\ capita_{i,t-1}$ | 0.079** | 0.082** | -0.013 |
| | (2.06) | (2.05) | (-1.40) |
| *Constant* | -3.201*** | -3.531*** | -2.665*** |
| | (-3.37) | (-3.80) | (-3.05) |
| *Province FE* | YES | YES | NO |
| *Year FE* | YES | YES | YES |
| *Industry FE* | YES | NO | YES |
| *Observations* | 2,158 | 2,160 | 2,158 |
| *R-squared* | 0.417 | 0.322 | 0.397 |

Note: This panel presents estimates from a regression model examining the relationship between *FBFTIS* and firms' *COD*, augmenting the control variable of technological capacity with measure of the number of patents granted. The dependent variable is *COD*. The main variable of interest is *FBFTIS*. Column 1 includes *Year, Industry*, and *Province* fixed effects, as well as all control variables. Columns 2 and 3 explore variations in fixed effects, with Column 2 including *Province* and *Year* fixed effects, and Column 3 including *Industry* and *Year* fixed effects. All explanatory variables lag by one year. Standard errors are clustered at the firm level and reported in parentheses beneath coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

**Panel B:**

| VARIABLES | (1)<br>$COD_{i,t}$ | (2)<br>$COD_{i,t}$ | (3)<br>$COD_{i,t}$ |
|---|---|---|---|
| $FBFTIS_{i,t-1}$ | -0.006* | -0.006* | -0.006* |
| | (-1.93) | (-1.84) | (-1.88) |
| $Ln\ (Total\ revenue)_{i,t-1}$ | -0.472*** | -0.389*** | -0.470*** |
| | (-6.32) | (-5.03) | (-6.23) |
| $Tobin's\ Q_{i,t-1}$ | -0.060* | -0.112*** | -0.078** |
| | (-1.89) | (-3.05) | (-2.46) |
| $PB_{i,t-1}$ | 0.014 | 0.033 | 0.022 |
| | (0.62) | (1.29) | (0.90) |
| $Firm\ Age_{i,t-1}$ | 0.254* | 0.232 | 0.316** |
| | (1.71) | (1.49) | (2.17) |
| $Liquid\ ratio_{i,t-1}$ | -0.211*** | -0.215*** | -0.206*** |
| | (-6.53) | (-6.70) | (-6.65) |
| $Size_{i,t-1}$ | 0.387*** | 0.316*** | 0.412*** |
| | (4.67) | (3.73) | (5.00) |
| $CaRexpr_{i,t-1}$ | 0.003 | 0.003 | 0.002 |

| | | | |
|---|---|---|---|
| | (1.34) | (1.36) | (1.07) |
| $CPI_{i,t-1}$ | 0.122 | 0.162* | 0.222*** |
| | (1.41) | (1.81) | (2.75) |
| $GDP\ per\ capita_{i,t-1}$ | 0.015 | 0.022 | 0.001 |
| | (0.31) | (0.44) | (0.12) |
| *Constant* | -1.861 | -2.117* | -2.719*** |
| | (-1.59) | (-1.81) | (-2.64) |
| *Province FE* | YES | YES | NO |
| *Year FE* | YES | YES | YES |
| *Industry FE* | YES | NO | YES |
| *Observations* | 1,161 | 1,168 | 1,161 |
| *R-squared* | 0.438 | 0.350 | 0.414 |

Note: This panel presents estimates from a regression model examining the relationship between *FBFTIS* and firms' *COD*, augmenting the control variable of technological capacity with measure of the ratio of capitalized research expenses to net profit. The dependent variable is *COD*. The main variable of interest is *FBFTIS*. Column 1 includes *Year, Industry*, and *Province* fixed effects, as well as all control variables. Columns 2 and 3 explore variations in fixed effects, with Column 2 including *Province* and *Year* fixed effects, and Column 3 including *Industry* and *Year* fixed effects. All explanatory variables lag by one year. Standard errors are clustered at the firm level and reported in parentheses beneath coefficient estimates. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

# Reference list:


Abadie, A. 2005. Semiparametric difference-in-differences estimators. ***The review of economic studies***, 72(1): 1-19.

Acharya, V. V., Schnabl, P., & Suarez, G. 2013. Securitization without risk transfer. ***Journal of Financial Economics***, 107(3): 515-536.

Adrian, T., & Ashcraft, A. B. 2012. Shadow banking regulation. ***Annu. Rev. Financ. Econ.***, 4(1): 99-140.

Aebi, V., Sabato, G. and Schmid, M., 2012. Risk management, corporate governance, and bank performance in the financial crisis. *Journal of Banking & Finance*, *36*(12), pp.3213-3226.Al-Ajlouni, A. 2018. ***Financial technology in banking industry: Challenges and opportunities***. Paper presented at the e International Conference on Economics and Administrative Sciences ICEAS2018.

Albastaki, Y., Razzaque, A., & Sarea, A. M. 2020. ***Innovative strategies for implementing FinTech in banking***: Hershey, Pennsylvania 701 E. Chocolate Avenue, Hershey, Pennsylvania, 17033, USA : IGI Global.

Albuquerque, B. 2024. Corporate debt booms, financial constraints, and the investment nexus. ***Journal of Applied Econometrics***, 39(5): 766-789.

Allen, F., Gu, X., & Jagtiani, J. 2020. A Survey of Fintech Research and Policy Discussion. ***ERN: Econometric Studies of Private Equity***.

Allen, F., Qian, J., & Qian, M. 2005. Law, finance, and economic growth in China. ***Journal of Financial Economics***, 77(1): 57-116.

An, J., & Rau, R. 2021. Finance, technology and disruption. ***The European Journal of Finance***, 27(4-5): 334-345.

An, P., & Yu, M. 2018. Neglected part of shadow banking in China. ***International Review of Economics & Finance***, 57: 211-236.

Aral, S., & Weill, P. 2007. IT Assets, Organizational Capabilities, and Firm Performance: How Resource Allocations and Organizational Differences

Explain Performance Variation. ***Organization Science***, 18(5): 763-780.

Ashraf, B. N. 2021. Is Economic Uncertainty a Risk Factor in Bank Loan Pricing Decisions? International Evidence. ***Risks***, 9(5): 81.

Ashraf, B. N., & Shen, Y. 2019. Economic policy uncertainty and banks' loan pricing. ***Journal of Financial Stability***, 44(C).

Atadoga, A., Farayola, O. A., Ayinla, B. S., Amoo, O. O., Abrahams, T. O., & Osasona, F. 2024. A comparative review of data encryption methods in the USA and Europe. ***Computer Science & IT Research Journal***, 5(2): 447-460.

Athanasoglou, P. P., Brissimis, S. N., & Delis, M. D. 2008. Bank-specific, industry-specific and macroeconomic determinants of bank profitability. ***Journal of International Financial Markets, Institutions and Money***, 18(2): 121-136.

Athari, S. A., Isayev, M., & Irani, F. 2024. Does country risk rating explain shadow banking development? Insights from advanced and emerging market economies. ***Economic Systems***, 48(2): 101192.

Avery, R. B., & Berger, A. N. 1991. Loan commitments and bank risk exposure. ***Journal of Banking & Finance***, 15(1): 173-192.

Avery, R. B., Bostic, R. W., & Samolyk, K. A. 1998. The role of personal wealth in small business finance. ***Journal of Banking & Finance***, 22(6-8): 1019-1061.

Avramidis, P., Asimakopoulos, I., Malliaropulos, D., & Travlos, N. G. 2021. Do banks appraise internal capital markets during credit shocks? Evidence from the Greek crisis. ***Journal of Financial Intermediation***, 45: 100855.

Baldenius, T., Deng, M., & Li, J. 2024. Accounting information and risk shifting with asymmetrically informed creditors. ***Journal of Accounting and Economics***, 77(2): 101667.

Bao, Z., & Huang, D. 2021. Shadow Banking in a Crisis: Evidence from Fintech During COVID-19. ***Journal of Financial and Quantitative Analysis***, 56(7): 2320-2355.

Barakova, I., Ehrentraud, J., & Leposke, L. 2024. ***A two-sided affair: banks and tech firms in banking***: Bank for International Settlements, Financial Stability Institute.

Bartlett, R. P. 2018. ***Consumer-Lending Discrimination in the Era of FinTech ****.

Basheer, M. F., Waemustafa, W., Hidthiir, M. H. B., & Hassan, S. G. 2021. Explaining the endogeneity between the credit risk, liquidity risk, and off-balance sheet activities in commercial banks: a case of South Asian economies. ***International Journal of Monetary Economics and Finance***, 14(2): 166-187.

Baule, R. 2014. Allocation of risk capital on an internal market. ***European Journal of Operational Research***, 234(1): 186-196.

Beck, T., Demirgüç-Kunt, A., Laeven, L., & Maksimovic, V. 2006. The determinants of financing obstacles. ***Journal of international money and finance***, 25(6): 932-952.

Behr, P. and Sonnekalb, S., 2012. The effect of information sharing between lenders on access to credit, cost of credit, and loan performance–Evidence from a credit registry introduction. *Journal of Banking & Finance*, *36*(11), pp.3017-3032.

Belhaj, M., Bourlès, R., & Deroïan, F. 2014. Risk-Taking and Risk-Sharing Incentives under Moral Hazard. ***American Economic Journal: Microeconomics***, 6(1): 58–90.

Bens, D. A., & Monahan, S. J. 2004. Disclosure Quality and the Excess Value of Diversification. ***Journal of Accounting Research***, 42(4): 691-730.

Berg, T., Burg, V., Gombović, A., & Puri, M. 2019. On the Rise of FinTechs: Credit Scoring Using Digital Footprints. ***The Review of Financial Studies***, 33(7): 2845-2897.

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

Berger, A. N., & Bouwman, C. H. S. 2013. How does capital affect bank performance during financial crises? ***Journal of financial economics***, 109(1): 146-176.

Berger, A. N., Curti, F., Mihov, A., & Sedunov, J. 2022. Operational Risk is More Systemic than You Think: Evidence from U.S. Bank Holding Companies. ***Journal of Banking & Finance***, 143: 106619.

Berger, A. N., & Humphrey, D. B. 1997. Efficiency of financial institutions: International survey and directions for future research. ***European journal of operational research***, 98(2): 175-212.

Berger, A. N., & Roman, R. A. 2015. Did TARP Banks Get Competitive Advantages? ***Journal of financial and quantitative analysis***, 50(6): 1199-1236.

Berger, A. N., & Udell, G. F. 1995. Relationship Lending and Lines of Credit in Small Firm Finance. ***The Journal of Business***, 68(3): 351-381.

Berríos, M.R., 2013. The relationship between bank credit risk and profitability and liquidity. *The International Journal of Business and Finance Research*, *7*(3), pp.105-118.

Bessler, W., Kurmann, P., & Nohel, T. 2015. Time-varying systematic and idiosyncratic risk exposures of US bank holding companies. ***Journal of International Financial Markets, Institutions and Money***, 35: 45-68.

Bhagat, S., Bolton, B., & Lu, J. 2015. Size, leverage, and risk-taking of financial institutions. ***Journal of Banking & Finance***, 59: 520-537.

Bharath, S. T., Sunder, J., & Sunder, S. V. 2008. Accounting Quality and Debt Contracting. ***The Accounting Review***, 83(1): 1-28.

Bian, W., Wang, S., & Xie, X. 2023. How valuable is FinTech adoption for traditional banks? ***European Financial Management***, 29(1).

Biguri, K., & Stahl, J. R. 2024. Collateral requirements and corporate policy decisions. ***Journal of Financial Intermediation***, 60: 101104.

Billett, M. T., & Mauer, D. C. 2003. Cross-Subsidies, External Financing Constraints, and the Contribution of the Internal Capital Market to Firm Value. ***The Review of Financial Studies***, 16(4): 1167-1201.

Birkinshaw, J., & Heywood, S. 2010. Putting organizational complexity in its place. ***McKinsey quarterly***, 3(6): 122-127.

Boot, A. 2016. Understanding the Future of Banking Scale and Scope Economies, and Fintech, ***The Future of Large, Internationally Active Banks***: 431-449: World Scientific Publishing Co. Pte. Ltd.

Brandt, L., & Li, H. 2003. Bank discrimination in transition economies: ideology, information, or incentives? ***Journal of Comparative Economics***, 31(3): 387-413.

Bratten, B., Causholli, M., & Omer, T. C. 2019. Audit Firm Tenure, Bank Complexity, and Financial Reporting Quality. ***Contemporary Accounting Research***, 36(1): 295-325.

Bromberg, L., Godwin, A., & Ramsay, I. 2017. Fintech sandboxes: Achieving a balance between regulation and innovation. ***Journal of Banking and Finance Law and Practice***, 28(4): 314-336.

Bu, S., Jeong, U. A., & Koh, J. 2022. Robotic Process Automation: A New Enabler for Digital Transformation and Operational Excellence. ***Business Communication Research and Practice***.

Buch, C. M., Koch, C. T., & Koetter, M. 2013. Do banks benefit from internationalization? Revisiting the market power–risk nexus. ***Review of Finance***, 17(4): 1401-1435.

Buchak, G., Matvos, G., Piskorski, T., & Seru, A. 2018. Fintech, regulatory arbitrage, and the rise of shadow banks. ***Journal of Financial Economics***, 130(3): 453-483.

Bushman, R. M., Piotroski, J. D., & Smith, A. J. 2004. What determines corporate transparency? ***Journal of accounting research***, 42(2): 207-252.

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

Butler, A. W., Cornaggia, J., & Gurun, U. G. 2017. Do Local Capital Market Conditions Affect Consumers' Borrowing Decisions? ***Management Science***, 63(12): 4175-4187.

Cao, L., Yang, Q., & Yu, P. S. 2021. Data science and AI in FinTech: An overview. ***International Journal of Data Science and Analytics***, 12(2): 81-99.

Cao, L., Yuan, G., Leung, T., & Zhang, W. 2020. Special issue on AI and FinTech: the challenge ahead. ***IEEE intelligent systems***, 35(2): 3-6.

Carbó Valverde, S., & Rodríguez Fernández, F. 2007. The determinants of bank margins in European banking. ***Journal of Banking & Finance***, 31(7): 2043-2063.

Carlini, F., Del Gaudio, B. L., Porzio, C., & Previtali, D. 2022. Banks, FinTech and stock returns. ***Finance Research Letters***, 45: 102252.

Cassar, G., Ittner, C. D., & Cavalluzzo, K. S. 2015. Alternative information sources and information asymmetry reduction: Evidence from small business debt. ***Journal of Accounting and Economics***, 59(2): 242-263.

Cetorelli, N., & Goldberg, L. S. 2014. Measures of global bank complexity. ***Economic policy review (Federal Reserve Bank of New York)***, 20(2): 107.

Cetorelli, N., & Goldberg, L. S. 2016. Organizational complexity and balance sheet management in global banks: National Bureau of Economic Research.

Cetorelli, N., McAndrews, J., & Traina, J. 2014. Evolution in bank complexity. ***Economic policy review (Federal Reserve Bank of New York)***, 20(2): 85.

Chang, J., Yang, T., & Shi, Y. 2022. Finance leases: In the shadow of banks. ***Review of Finance***, 26(3): 721-749.

Chen, M., Jeon, B. N., Wang, R., & Wu, J. 2015. Corruption and bank risk-taking: Evidence from emerging economies. ***Emerging Markets Review***, 24: 122-148.

Chen, W., Wu, W., & Zhang, T. 2023. Fintech development, firm digitalization, and bank loan pricing. ***Journal of Behavioral and Experimental Finance***, 39: 100838.

Chen, Y., & Bellavitis, C. 2020. Blockchain disruption and decentralized finance: The rise of decentralized business models. ***Journal of Business Venturing Insights***, 13: e00151.

Chen, Z. 2019. The Long-term rate and interest rate volatility in monetary policy transmission. ***Available at SSRN 3462101***.

Cheng, M., & Qu, Y. 2020. Does bank FinTech reduce credit risk? Evidence from China. ***Pacific-Basin Finance Journal***, 63: 101398.

Chernenko, S., Erel, I., & Prilmeier, R. 2018. Nonbank lending.

Chiorazzo, V., D'Apice, V., DeYoung, R., & Morelli, P. 2018. Is the traditional banking model a survivor? ***Journal of Banking & Finance***, 97: 238-256.

Christiansen, W. A., & Pace, D. 1994. Relaxing the Glass-Steagall Act: Do Diversification Benefits Exist. ***Journal of Financial and Strategic Decisions***, 7(3): 55-62.

Citterio, A., King, T., & Locatelli, R. 2024. Is digital transformation profitable for banks? Evidence from Europe. ***Finance Research Letters***, 70: 106269.

Cole, R. A., & White, L. J. 2012. Déjà vu all over again: the causes of U.S. commercial bank failures this time around. ***Journal of Financial Services Research***, 42(1–2): 5–29.

Correa, R., & Goldberg, L. S. 2022. Bank complexity, governance, and risk. ***Journal of Banking & Finance***, 134: 106013.

Croux, C., Jagtiani, J., Korivi, T., & Vulanovic, M. 2020. Important factors determining Fintech loan default: Evidence from a lendingclub consumer platform. ***Journal of Economic Behavior & Organization***, 173: 270-296.

Cvitanić, J., Possamaï, D., & Touzi, N. 2017. Moral Hazard in Dynamic Risk Management. ***Management Science***, 63(10): 3328-3346.

Dam, L., & Koetter, M. 2012. Bank bailouts and moral hazard: Evidence from Germany. ***The Review of Financial Studies***, 25(8): 2343-2380.

Das, S. R. 2019. The future of fintech. ***Financial Management***, 48(4): 981-1007.

Dehejia, R. H. 2005. Program evaluation as a decision problem. ***Journal of Econometrics***, 125(1-2): 141-173.

Dell'Ariccia, G., Laeven, L., & Marquez, R. 2014. Real interest rates, leverage, and bank risk-taking. ***Journal of Economic Theory***, 149: 65-99.

Demirgüç-Kunt, A., & Huizinga, H. 1999. Determinants of Commercial Bank Interest Margins and Profitability: Some International Evidence. ***The World Bank Economic Review***, 13(2): 379-408.

Demirkan, I., & Demirkan, S. 2012. Network Characteristics and Patenting in Biotechnology, 1990-2006. ***Journal of Management***, 38(6): 1892-1927.

Deng, S., & Elyasiani, E. 2008. Geographic diversification, bank holding company value, and risk. ***Journal of Money, Credit and Banking***, 40(6): 1217-1238.

Diamond, D. W. 1984. Financial intermediation and delegated monitoring. ***The review of economic studies***, 51(3): 393-414.

Dimick, J. B., & Ryan, A. M. 2014. Methods for evaluating changes in health care policy: the difference-in-differences approach. ***Jama***, 312(22): 2401-2402.

Ding, N., Fung, H.-G., & Jia, J. 2020. Shadow banking, bank ownership, and bank efficiency in China. ***Emerging Markets Finance and Trade***, 56(15): 3785-3804.

Ding, N., Gu, L., & Peng, Y. 2022. Fintech, financial constraints and innovation: Evidence from China. ***Journal of Corporate Finance***, 73: 102194.

Dong, X., & Yu, M. 2023. Does FinTech development facilitate firms' innovation? Evidence from China. ***International Review of Financial Analysis***, 89: 102805.

Du, J., Li, C., & Wang, Y. 2023. Shadow banking of non-financial firms: Arbitrage between formal and informal credit markets in China. ***Journal of Financial Intermediation***, 55: 101032.

Duan, Y., El Ghoul, S., Guedhami, O., Li, H., & Li, X. 2021. Bank systemic risk around COVID-19: A cross-country analysis. ***Journal of Banking & Finance***, 133: 106299.

Duchin, R., & Sosyura, D. 2014. Safer ratios, riskier portfolios: Banks′ response to government aid. ***Journal of Financial Economics***, 113(1): 1-28.

Duru, A., & Reeb, D. M. 2002. International Diversification and Analysts' Forecast Accuracy and Bias. ***The Accounting Review***, 77(2): 415-433.

Elia, G., Stefanelli, V., & Ferilli, G. B. 2023. Investigating the role of Fintech in the banking industry: what do we know? ***European Journal of Innovation Management***, 26(5): 1365-1393.

Ellul, A. and Yerramilli, V., 2013. Stronger risk controls, lower risk: Evidence from US bank holding companies. *The journal of finance*, *68*(5), pp.1757-1803.

Elsaid, H. M. 2023. A review of literature directions regarding the impact of fintech firms on the banking industry. ***Qualitative Research in Financial Markets***, 15(5): 693-711.

Engelen, C. 2015. The effects of managerial discretion on moral hazard related behaviour: German evidence on agency costs. ***Journal of Management & Governance***, 19(4): 927-960.

English, W. B. 2002. Interest rate risk and bank net interest margins. ***BIS Quarterly Review***, 10(1): 67-82.

Erel, I., & Liebersohn, J. 2022. Can FinTech reduce disparities in access to finance? Evidence from the Paycheck Protection Program. ***Journal of Financial Economics***, 146(1): 90-118.

Fernholz, R. T., & Koch, C. 2017. Big banks, idiosyncratic volatility, and systemic risk. ***American Economic Review***, 107(5): 603-607.

Ferrara, E. L., Chong, A., & Duryea, S. 2012. Soap operas and fertility: Evidence from Brazil. ***American Economic Journal: Applied Economics***, 4(4): 1-31.

Fosu, S., Ntim, C. G., Coffie, W., & Murinde, V. 2017. Bank opacity and risk-taking: Evidence from analysts' forecasts. ***Journal of Financial Stability***, 33: 81-95.

Fraisse, H., Lé, M., & Thesmar, D. 2019. The Real Effects of Bank Capital Requirements. ***Management Science***, 66(1): 5-23.

Freixas, X., Lóránth, G., & Morrison, A. D. 2007. Regulating financial conglomerates. ***Journal of Financial Intermediation***, 16(4): 479-514.

Freixas, X., & Santomero, A. 2002. An overall perspective on banking regulation. Federal Reserve Bank of Philadephia: Working Paper 02-1.

FSB 2012 ***Global Shadow Banking Monitoring Report*** https://www.fsb.org/wp-content/uploads/r_121118c.pdf

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

Gallimberti, C. M. 2021. Borrowers' Financial Reporting and the Quality of Banks' Loan Portfolios. ***The Accounting Review***, 96(2): 261-301.

García-Kuhnert, Y., Marchica, M.-T., & Mura, R. 2015. Shareholder diversification and bank risk-taking. ***Journal of Financial Intermediation***, 24(4): 602-635.

Geng, H., Cheng, M., & Zhang, J. 2021. Effects of wealth management products on bank risk in China: The role of audit committee effectiveness. ***Pacific Economic Review***, 26(5): 575-616.

Gennaioli, N., Shleifer, A., & Vishny, R. 2012. Neglected risks, financial innovation, and financial fragility. ***Journal of financial economics***, 104(3): 452-468.

Gennaioli, N., Shleifer, A., & Vishny, R. W. 2013. A model of shadow banking. ***The Journal of Finance***, 68(4): 1331-1363.

Ghosh, S., Gonzalez del Mazo, I., & Ötker-Robe, İ. 2012. Chasing the shadows: How significant is shadow banking in emerging markets? ***World Bank-Economic Premise***(88): 1-7.

Giglio, F. 2022. Fintech: A literature review. ***International Business Research***, 15(1): 80-85.

Goetz, M. R., Laeven, L., & Levine, R. 2016. Does the geographic expansion of banks reduce risk? ***Journal of Financial Economics***, 120(2): 346-362.

Goldstein, I., Jiang, W., & Karolyi, G. A. 2019. To FinTech and Beyond. ***The Review of Financial Studies***, 32(5): 1647-1661.

González-Páramo, J. M. 2017. ***Financial innovation in the digital age: challenges for regulation and supervision***.

Gopal, M., & Schnabl, P. 2022. The Rise of Finance Companies and FinTech Lenders in Small Business Lending. ***The Review of Financial Studies***, 35(11): 4859-4901.

Gorton, G. B., & Souleles, N. S. 2007. Special purpose vehicles and securitization, ***The risks of financial institutions***: 549-602: University of Chicago Press.

Guerra, P., & Castelli, M. 2021. Machine learning applied to banking supervision a literature review. ***Risks***, 9(7): 136.

Guo, X., Li, M., Wang, Y., & Mardani, A. 2023. Does digital transformation improve the firm's performance? From the perspective of digitalization paradox and managerial myopia. ***Journal of Business Research***, 163: 113868.

Ha, L. T. 2022. Effects of digitalization on financialization: Empirical evidence from

European countries. ***Technology in Society***, 68: 101851.

Haq, M., Tripe, D., & Seth, R. 2022. Do traditional off-balance sheet exposures increase bank risk? ***Journal of International Financial Markets, Institutions and Money***, 80: 101627.

Hasan, M., Hoque, A., & Le, T. 2023. Big Data-Driven Banking Operations: Opportunities, Challenges, and Data Security Perspectives. ***FinTech***, 2(3): 484-509.

Hasman, A., & Samartín, M. 2022. Leaving the darkness: The emergence of shadow banks. ***Journal of Financial Stability***, 61: 101039.

Hassan, M. K. 1993. The off-balance sheet banking risk of large U.S. commercial banks. ***The Quarterly Review of Economics and Finance***, 33(1): 51-69.

Hassan, M. K., Karels, G. V., & Peterson, M. O. 1993. Off-balance sheet activities and bank default-risk premia: a comparison of risk measures. ***Journal of Economics and Finance***, 17: 69-83.

Hassan, M. K., & Sackley, W. H. 1994. A methodological investigation of risk exposure of bank off-balance sheet loan commitment activities. ***The Quarterly Review of Economics and Finance***, 34(3): 283-299.

He, C., Geng, X., Tan, C., & Guo, R. 2023. Fintech and corporate debt default risk: Influencing mechanisms and heterogeneity. ***Journal of Business Research***, 164: 113923.

Heap, B., Pollari, I., H2 Ventures, & KPMG. 2017. ***FINTECH100 Leading global fintech innovators***. https://assets.kpmg.com/content/dam/kpmg/qm/pdf/H2-Fintech-Innovators-2017.pdf.

Heckman, J. J. 1979. Sample selection bias as a specification error. ***Econometrica: Journal of the econometric society***: 153-161.

Hendry, J. 2005. Beyond Self-Interest: Agency Theory and the Board in a Satisficing World. ***British Journal of Management***, 16(s1): S55-S63.

Heo, Y. 2023. Cybersecurity and Bank Distance-to-Default. ***Available at SSRN***

***4660090***.

Herpfer, C. 2021. The role of bankers in the US syndicated loan market. ***Journal of Accounting and Economics***, 71(2-3): 101383.

Ho, D. E., Imai, K., King, G., & Stuart, E. A. 2007. Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. ***Political analysis***, 15(3): 199-236.

Ho, K., Wong, E., & Tan, E. 2022. Complexity of global banks and the implications for bank risk: Evidence from foreign banks in Hong Kong. ***Journal of Banking & Finance***, 134: 106034.

Hodula, M., & Ngo, N. A. 2024. Does macroprudential policy leak? Evidence from shadow bank lending in EU countries. ***Economic Modelling***, 132: 106657.

Holland, C. P., Lockett, A. G., & Blackman, I. D. 1997. The impact of globalisation and information technology on the strategy and profitability of the banking industry, Vol. 3: 418-427 vol.413: IEEE.

Houston, J., James, C., & Marcus, D. 1997. Capital market frictions and the role of internal capital markets in banking. ***Journal of Financial Economics***, 46(2): 135-164.

Hu, D., Zhao, S., & Yang, F. 2024. Will fintech development increase commercial banks risk-taking? Evidence from China. ***Electronic Commerce Research***, 24(1): 37-67.

IFRS ***- IFRS 9 Financial Instruments***. 2025 . https://www.ifrs.org/issued-standards/list-of-standards/ifrs-9-financial-instruments/.

Jagtiani, J., & Khanthavit, A. 1996. Scale and scope economies at large banks: Including off-balance sheet products and regulatory effects (1984–1991). ***Journal of Banking & Finance***, 20(7): 1271-1287.

Jagtiani, J., & Lemieux, C. 2019. The roles of alternative data and machine learning in fintech lending: Evidence from the LendingClub consumer platform. ***Financial Management***, 48(4): 1009-1029.

Jalal, A., Al Mubarak, M., & Durani, F. 2023. Financial technology (fintech), ***Artificial***

***intelligence and transforming digital marketing***: 525-536: Springer.

Jarrow, R. A. 2008. Operational risk. ***Journal of Banking & Finance***, 32(5): 870-879.

Jiang, L., Levine, R., & Lin, C. 2023. Does Competition Affect Bank Risk? ***Journal of Money, Credit and Banking***, 55(5): 1043-1076.

Jiang, S., Cuesta, J. I., Jørring, A., & Xu, D. 2023. Bank Technology Adoption and Loan Production in the US Mortgage Market. ***Available at SSRN 4455105***.

Kalda, A., Pearson, C. G., & Sovich, D. 2023. Pass-Through in Lending: Evidence from Mortgages. ***SSRN Electronic Journal***.

Kambhu, J., Stiroh, K. J., & Schuermann, T. 2007. Hedge funds, financial intermediation, and systemic risk. ***FRB of New York Staff Report***(291).

Karim, S., & Lucey, B. M. 2024. BigTech, FinTech, and banks: A tangle or unity? ***Finance Research Letters***, 64: 105490.

Karkošková, S. 2023. Data governance model to enhance data quality in financial institutions. ***Information Systems Management***, 40(1): 90-110.

Kayed, S., Alta'any, M., Meqbel, R., Khatatbeh, I. N., & Mahafzah, A. 2024. Bank FinTech and bank performance: evidence from an emerging market. ***Journal of Financial Reporting and Accounting***.

Kim, J.-B., Simunic, D. A., Stein, M. T., & YI, C. H. 2011. Voluntary Audits and the Cost of Debt Capital for Privately Held Firms: Korean Evidence. ***Contemporary Accounting Research***, 28(2): 585-615.

Koeplin, J. P., & Lélé, P. 2023. Human capital management accounting issues for SOX compliance with Basel III final framework operational risk standards. ***Journal of Corporate Accounting & Finance***, 34(1): 9-20.

Krahnen, J.-P., Noth, F., & Schüwer, U. 2017. Structural reforms in banking: the role of trading. ***Journal of Financial Regulation***, 3(1): 66-88.

Kurt, A. C. 2018. How Do Financial Constraints Relate to Financial Reporting Quality? Evidence from Seasoned Equity Offerings. ***European Accounting Review***, 27(3): 527-557.

Kutzbach, M. J., & Pogach, J. 2024. Financial technology and relationship lending:

Complements or substitutes? ***Journal of Financial Intermediation***, 59: 101101.

Laeven, L., & Levine, R. 2007. Is there a diversification discount in financial conglomerates? ***Journal of financial economics***, 85(2): 331-367.

Laeven, L., & Levine, R. 2009. Bank governance, regulation and risk taking. ***Journal of financial economics***, 93(2): 259-275.

Le, T., Ngo, T., Nguyen, D. T., & Do, T. T. 2024. Fintech and banking: friends or foes? Evidence from bank–fintech cooperation. ***International Journal of Bank Marketing***(ahead-of-print).

Lee, C.-C., Li, X., Yu, C.-H., & Zhao, J. 2021. Does fintech innovation improve bank efficiency? Evidence from China's banking industry. ***International Review of Economics & Finance***, 74: 468-483.

Lee, C.-C., Ni, W., & Zhang, X. 2023. FinTech development and commercial bank efficiency in China. ***Global Finance Journal***, 57: 100850.

Lennox, C. S., Francis, J. R., & Wang, Z. 2012. Selection models in accounting research. ***The accounting review***, 87(2): 589-616.

Li, G., Elahi, E., & Zhao, L. 2022. Fintech, Bank Risk-Taking, and Risk-Warning for Commercial Banks in the Era of Digital Technology. ***Front Psychol***, 13: 934053.

Li, J., Li, J., Zhu, X., Yao, Y., & Casu, B. 2020. Risk spillovers between FinTech and traditional financial institutions: Evidence from the US. ***International Review of Financial Analysis***, 71: 101544.

Li, X., & Lin, J.-H. 2016. Shadow-banking entrusted loan management, deposit insurance premium, and capital regulation. ***International Review of Economics & Finance***, 41: 98-109.

Liang, H.-Y., Chen, I.-J., & Chen, S.-S. 2016. Does corporate governance mitigate bank diversification discount? ***International Review of Economics & Finance***, 45: 129-143.

Liberti, J. M., & Mian, A. R. 2008. Estimating the effect of hierarchies on information use. ***The Review of Financial Studies***, 22(10): 4057-4090.

Linn, M., & Weagley, D. 2024. Uncovering Financial Constraints. ***Journal of***

***Financial and Quantitative Analysis***, 59(6): 2582-2617.

Loutskina, E. 2011. The role of securitization in bank liquidity and funding management. ***Journal of Financial Economics***, 100(3): 663-684.

Lu, Y., & Nikolaev, V. V. 2022. Expected Loan Loss Provisioning: An Empirical Model. ***The Accounting Review***, 97(7): 319-346.

Lv, P., & Xiong, H. 2022. Can FinTech improve corporate investment efficiency? Evidence from China. ***Research in International Business and Finance***, 60: 101571.

Marcelin, I., Sun, W., Teclezion, M., & Junarsin, E. 2022. Financial inclusion and bank risk-taking: the effect of information sharing. ***Finance Research Letters***, 50: 103182.

Margiotta, M. M., & Miller, R. A. 2000. Managerial Compensation and the Cost of Moral Hazard. ***International Economic Review***, 41(3): 669-719.

Marinelli, G., Nobili, A., & Palazzo, F. 2022. The multiple dimensions of bank complexity: Effects on credit risk-taking. ***Journal of Banking & Finance***, 134: 106039.

Martynova, N., & Vogel, U. 2022. Banks' complexity-risk nexus and the role of regulation. ***Journal of Banking & Finance***, 134: 106120.

Merritt, R. 2013. Why is the accrual basis of accounting accepted by GAAP. ***Chron. com (< http://www. smallbusiness. chron. com/accrual-basis-accounting-accepted-gaap-63890. html>)***.

Milcheva, S., Falkenbach, H., & Markmann, H. 2019. Bank liquidity management through the issuance of bonds in the aftermath of the global financial crisis. ***Research in International Business and Finance***, 48: 32-47.

Minsky, H. P. 1986. Stabilizing an Unstable Economy.

Mishkin, F. S. 2006. How big a problem is too big to fail? A review of Gary Stern and Ron Feldman's too big to fail: the hazards of bank bailouts. ***Journal of economic literature***, 44(4): 988-1004.

Moch, N. 2018. The contribution of large banking institutions to systemic risk: What do we know? A literature review. ***Review of Economics***, 69(3): 231-257.

Mohsni, S. and Otchere, I., 2014. Risk taking behavior of privatized banks. Journal of Corporate Finance, 29, pp.122-142.

Molnár, J. 2018. What does financial intermediation theory tell us about fintechs? ***Vezetéstudomány-Budapest Management Review***, 49(5): 38-46.

Mourouzidou-Damtsa, S., Milidonis, A. and Stathopoulos, K., 2019. National culture and bank risk-taking. *Journal of Financial Stability*, *40*, pp.132-143.

Mukherjee, T., & Pana, E. 2018. The distribution of the Capital Purchase Program funds: Evidence from bank internal capital markets. ***Financial Markets, Institutions & Instruments***, 27(4): 125-143.

Murinde, V., Rizopoulos, E., & Zachariadis, M. 2022. The impact of the FinTech revolution on the future of banking: Opportunities and risks. ***International Review of Financial Analysis***, 81: 102103.

Naiki, E., & Ogane, Y. 2024. Main bank impairment and corporate cash holdings during the global financial crisis. ***Journal of Corporate Finance***, 86: 102565.

Najaf, K., Mostafiz, M. I., & Najaf, R. 2021. Fintech firms and banks sustainability: why cybersecurity risk matters? ***International Journal of Financial Engineering***, 8(02): 2150019.

Nguyen, T. L., Nguyen, T. C., & Ho, T. T. 2024. The effects of corporate taxation on the cost of bank loans. ***Applied Economics Letters***, 31(21): 2244-2249.

Omarova, S. T. 2020. Technology v technocracy: Fintech as a regulatory challenge. ***Journal of Financial Regulation***, 6(1): 75-124.

Oyewole, A. T., & Adegbite, M. 2023. The impact of Artificial Intelligence(AI), Blockchain, Cloud Computing and Data Analytics on the future of the Fintech Industry in the US. ***SSRN Electronic Journal***.

Pagano, M., & Volpin, P. 2012. Securitization, disclosure and liquidity. ***Review of Financial Studies***, 25(8): 2417-2453.

Patenge, R., Anand, A. & Goel, R. 2024. Managing bank IT spending: Five questions for tech leaders. October 18. ***McKinsey &***

***Company***. https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/tech-forward/managing-bank-it-spending-five-questions-for-tech-leaders.

Penas, M. F., & Unal, H. 2004. Gains in bank mergers: Evidence from the bond markets. ***Journal of Financial Economics***, 74(1): 149-179.

Petersen, M. A., & Rajan, R. G. 1994. The benefits of lending relationships: Evidence from small business data. ***The journal of finance***, 49(1): 3-37.

Philippon, T. 2016. The Fintech Opportunity. National Bureu of Economic research.

Plantin, G. 2015. Shadow banking and bank capital regulation. ***The Review of Financial Studies***, 28(1): 146-175.

Puschmann, T. 2017. Fintech. ***Business & information systems engineering***, 59(1): 69-76.

Rajan, R. G., & Zingales, L. 2001. The firm as a dedicated hierarchy: A theory of the origins and growth of firms. ***The Quarterly Journal of Economics***, 116(3): 805-851.

Reiter, M., & Zessner-Spitzenberg, L. 2023. Long-term bank lending and the transfer of aggregate risk. ***Journal of Economic Dynamics and Control***, 151: 104651.

Rerung, A., Paranita, E. S., AY, R. A. A., Budiandru, B., & Tandililing, E. M. 2024. The Influence of Fintech Innovations, ESG Reporting, and Blockchain Technology on Financial Transparency and Accountability. ***The Journal of Academic Science***, 1(2): 111-117.

Rochet, J.-C. 2004. Bank runs and financial crises: a discussion. ***Credit Intermediation and the Macro Economy, Oxford University Press, Oxford, UK***.

Rosenbaum, P. R., Rosenbaum, P., & Briskman. 2010. ***Design of observational studies***: Springer.

Rosenbaum, P. R., & Rubin, D. B. 1983. The central role of the propensity score in observational studies for causal effects. ***Biometrika***, 70(1): 41-55.

Roth, J. 2022. Pretest with caution: Event-study estimates after testing for parallel trends. ***American Economic Review: Insights***, 4(3): 305-322.

Rubin, D. B. 2007. The design versus the analysis of observational studies for causal effects: parallels with the design of randomized trials. ***Statistics in medicine***, 26(1): 20-36.

Sakai, K., Uesugi, I., & Watanabe, T. 2010. Firm age and the evolution of borrowing costs: Evidence from Japanese small firms. ***Journal of Banking & Finance***, 34(8): 1970-1981.

Santos, J. 2000. Bank capital regulation in contemporary banking theory: a review of the literature Working Paper. ***Bank for International Settlement***.

Scharfstein, D. S., & Stein, J. C. 2000. The Dark Side of Internal Capital Markets: Divisional Rent-Seeking and Inefficient Investment. ***The Journal of Finance***, 55(6): 2537-2564.

Schmid, M. M., & Walter, I. 2009. Do financial conglomerates create or destroy economic value? ***Journal of Financial Intermediation***, 18(2): 193-216.

Sengupta, P. 1998. Corporate disclosure quality and the cost of debt. ***Accounting review***: 459-474.

Sensarma, R. and Jayadev, M., 2009. Are bank stocks sensitive to risk management?. *The journal of risk finance*, *10*(1), pp.7-22.Siek, M., & Sutanto, A. 2019. ***Impact Analysis of Fintech on Banking Industry***. Paper presented at the 2019 International Conference on Information Management and Technology (ICIMTech).

Siggelkow, N., & Rivkin, J. W. 2005. Speed and search: Designing organizations for turbulence and complexity. ***Organization science***, 16(2): 101-122.

Skrastins, J., & Vig, V. 2019. How organizational hierarchy affects information production. ***The Review of Financial Studies***, 32(2): 564-604.

Stein, J. C. 2002. Information production and capital allocation: Decentralized versus hierarchical firms. ***The journal of finance***, 57(5): 1891-1921.

Stiroh, K.J., 2006. New evidence on the determinants of bank risk. *Journal of Financial Services Research*, *30*(3), pp.237-263.

Stock, J., & Yogo, M. 2005. Asymptotic distributions of instrumental variables statistics with many instruments. ***Identification and inference for econometric models: Essays in honor of Thomas Rothenberg***, 6: 109-120.

Stuart, E. A. 2010. Matching methods for causal inference: A review and a look forward. ***Statistical science: a review journal of the Institute of Mathematical Statistics***, 25(1): 1.

Stuart, E. A., Huskamp, H. A., Duckworth, K., Simmons, J., Song, Z., Chernew, M. E., & Barry, C. L. 2014. Using propensity scores in difference-in-differences models to estimate the effects of a policy change. ***Health Services and Outcomes Research Methodology***, 14: 166-182.

Stulz, R. M. 2019. Fintech, bigtech, and the future of banks. ***Journal of Applied Corporate Finance***, 31(4): 86-97.

Sun, J., & Liu, G. 2014. Audit committees' oversight of bank risk-taking. ***Journal of Banking & Finance***, 40: 376-387.

Sungau, J., & Ndunguru, P. C. 2015. Business Process Re-engineering: A Panacea for Reducing Operational Cost in Service Organizations. ***Independent Journal of Management & Production***, 6: 141-168.

Tarawneh, A., Abdul-Rahman, A., Mohd Amin, S. I., & Ghazali, M. F. 2024. A systematic review of fintech and banking profitability. ***International Journal of Financial Studies***, 12(1): 3.

Thakor, A. V. 2020. Fintech and banking: What do we know? ***Journal of Financial Intermediation***, 41: 100833.

Tyler, B. B. 2001. The complementarity of cooperative and technological competencies: a resource-based perspective. ***Journal of Engineering and Technology Management***, 18(1): 1-27.

Uzun, H., & Webb, E. 2007. Securitization and risk: empirical evidence on US banks. ***The Journal of Risk Finance***, 8(1): 11-23.

Valta, P. 2012. Competition and the cost of debt. ***Journal of Financial Economics***, 105(3): 661-682.

Varotto, S. 2011. Liquidity risk, credit risk, market risk and bank capital. ***International***

***Journal of Managerial Finance***, 7(2): 134-152.

Wang, C.-W., Chiu, W.-C., & King, T.-H. D. 2020. Debt maturity and the cost of bank loans. ***Journal of Banking & Finance***, 112: 105235.

Wang, H., Mao, K., Wu, W., & Luo, H. 2023a. Fintech inputs, non-performing loans risk reduction and bank performance improvement. ***International Review of Financial Analysis***, 90: 102849.

Wang, J., Huang, X., Gu, Q., Song, Z., & Sun, R. 2023b. How does fintech affect bank risk? A perspective based on financialized transfer of government implicit debt risk. ***Economic Modelling***, 128: 106498.

Wang, J., & Wang, L. 2024. When shareholders cross-hold lenders' equity: The effects on the costs of bank loans. ***Journal of Banking & Finance***, 163: 107189.

Wang, R., Liu, J., & Luo, H. 2021. Fintech development and bank risk taking in China. ***The European Journal of Finance***, 27(4-5): 397-418.

Wang, Y., & Wu, S. 2024. Impact of mobile banking on small business lending after bank branch closures. ***Journal of Corporate Finance***, 87: 102593.

West, M. A., & Anderson, N. R. 1996. Innovation in top management teams. ***Journal of Applied Psychology***, 81(6): 680-693.

Wiktor, M. Z., & Wadeusz, X. W. 2025. How Banks Leverage Digital Transformation to Mitigate Deposit Outflows Driven by P2P Lending Platforms. ***Journal of World Economy***, 4(1): 35-40.

Wooldridge, B., Schmid, T., & Floyd, S. W. 2008. The Middle Management Perspective on Strategy Process: Contributions, Synthesis, and Future Research. ***Journal of Management***, 34(6): 1190-1221.

Wu, J., Yan, Y., Chen, M., & Jeon, B. N. 2022. Monetary policy, economic uncertainty and bank risk: Cross-country evidence. ***Journal of International Money and Finance***, 122: 102580.

Wu, M.-W., & Shen, C. H. 2019. Effects of shadow banking on bank risks from the view of capital adequacy. ***International Review of Economics & Finance***, 63: 176-197.

Wu, X., Jin, T., Yang, K., & Qi, H. 2023. The impact of bank FinTech on commercial banks' risk-taking in China. ***International Review of Financial Analysis***, 90: 102944.

Wu, Z., Pathan, S., & Zheng, C. 2024. FinTech adoption in banks and their liquidity creation. ***The British Accounting Review***: 101322.

Zhang, D., Cai, J., Dickinson, D. G., & Kutan, A. M. 2016. Non-performing loans, moral hazard and regulation of the Chinese commercial banking system. ***Journal of Banking & Finance***, 63: 48-60.

Zhang, J., & Malikov, E. 2022. Off-balance sheet activities and scope economies in U.S. banking. ***Journal of Banking & Finance***, 141: 106534.

Zhang, Q., Chen, S., & Jin, Y. 2020. The impact of off-balance-sheet regulations on bank risk-taking: Evidence from China. ***Research in International Business and Finance***, 54: 101297.

Zhang, Q., Que, J., & Qin, X. 2023. Regional financial technology and shadow banking activities of non-financial firms: Evidence from China. ***Journal of Asian Economics***, 86: 101606.