Kobe University Repository : Kernel

PDF issue: 2026-11-30

Diversification, Complexity, and Bank Performance: Evidence from Japan

伍, 一昌

(Degree)
博士（商学）

(Date of Degree)
2024-03-25

(Date of Publication)
2026-03-25

(Resource Type)
doctoral thesis

(Report Number)
甲第8844号

(URL)
https://hdl.handle.net/20.500.14094/0100490069

※ 当コンテンツは神戸大学の学術成果です。無断複製・不正使用等を禁じます。著作権法で認められている範囲内で、適切にご利用ください。

Doctoral Dissertation

Diversification, Complexity and Bank Performance: Evidence from Japan
銀行の多様化・複雑性と経営パフォーマンスとの関係：日本からの証拠

January 19th, 2024
Graduate School of Business Administration
Kobe University
UCHIDA Laboratory
Business Administration
195B410B
YICHANG Wu
(伍　一昌)

Contents

Chapter 1 Overview of dissertation 1

Chapter 2 Bank diversification and performance: Evidence from Japan 8

2.1. Introduction 9

2.2. Understanding the background of bank diversification in Japan 14
2.2.1 The segmentation of Japanese banking sector 14
2.2.2 The decrease in interest spread 15
2.2.3 Deregulation and competition from other industries 16

2.3. Literature review 17
2.3.1 Profitability, firm value, and bank diversification 17
2.3.2 Risk and bank diversification 19

2.4. Data and methodology 21
2.4.1 Data 21
2.4.2 Methodology 22
2.4.3 Variables 22

2.5. Empirical results 27
2.5.1 Profitability and bank diversification 27
2.5.2 Risk and bank diversification 30
2.5.3 Endogeneity 31
2.5.4 Additional robustness tests 33

2.6. Further analysis 35
2.6.1 The effects of bank types 35
2.6.2 The decomposition of non-interest income 37
2.6.3 Bank diversification effects during the crisis 38

2.7. Conclusion 39

Tables 42

Figures 54

Appendix 55

References 57

Chapter 3 Economies of scope in the Japanese banking industry 60

3.1. Introduction 61

3.2. Literature review 64

3.3. Methodology and data 66
3.3.1 Outputs, inputs, and price variables 66
3.3.2 Cost function and estimation 68
3.3.3 Measures for economies of scope 70
3.3.4 Data 74

3.4. Results 75
3.4.1 Estimates of economies of scope 75
3.4.2 Estimates of economies of diversification 77
3.4.3 Diversification and economies of scope 79

3.5. Robustness 82
3.5.1 Conventional estimates of economies of scope 82
3.5.2 Estimates without city banks 83
3.5.3 Net non-interest income as a measure of off-balance sheet activities 83
3.5.4 Fourier flexible function 84

3.6. Conclusion 86

Tables **88**

Figures **98**

Appendix 1 ..... **99**

1.1 Economies of diversification 99

1.2 Decomposition of economies of diversification 100

Appendix 2 ..... **102**

Reference **103**

Chapter 4 Bank complexity, performance, and governance: Evidence from Japan **106**

4.1. Introduction **107**

4.2. literature review and hypothesis development **112**

4.2.1 The metrics of bank complexity 112

4.2.2 Complexity, bank value, and risk 114

4.2.3 Complexity, bank value, and risk: the moderating effect of governance 117

4.3. Data and methodology **118**

4.3.1 Data 118

4.3.2 Empirical specification 120

4.3.3 Variables 120

4.3.4 Summary statistics 126

4.4. Empirical results **128**

4.4.1 Complexity and bank performance 128

4.4.2 Governance, bank performance, and moderating effects 130

4.4.3 Additional robustness test 133

4.5. Further analysis **135**

4.5.1 Channels analysis 135

4.5.2 Does bank size matter? 138

4.6. Conclusion **139**

Tables **141**

Figures **158**

Appendix 1 ..... **160**

Appendix 2 ..... **162**

Reference **163**

Chapter 5 Conclusion **166**

Acknowledgment

I would like to express my sincere gratitude to the following people and organizations.

Firstly, I extend my deepest appreciation to my supervisor, Professor Hirofumi Uchida. As a graduate student from China, Professor Uchida provided me with the opportunity to study at Kobe University and offered invaluable guidance on starting and improving my research. The Uchida Zemi provided an environment where I could freely expand my studies and receive prompt feedback. Also, Professor Uchida's unwavering support in providing access to important database, significantly contributed to the completion of this dissertation.

Secondly, I would like to thank other professors for their valuable advice. Special appreciation goes to Professor Kenya Fujiwara and Professor Takashi Hatakeda, the vice chair of my dissertation committee, as well as Professor Takashi Yamasaki and Professor Naoya Mori in the Joint Zemi. I am grateful to Professor Yoshiaki Ogura (Waseda University), Professor Michiru Sawada (Nihon University), and Professor Takayoshi Nakaoka (Kindai University) for their valuable comments on the conference presentations, and Professor Kozo Harimaya (Ritsumeikan University) for insights into collaborative research.

Moreover, I extend my gratitude to my family and friends for their support and encouragement in my life.

Finally, my thanks would go to the staff in Business administration at Kobe University, and in particular, the "Next-Generation Outstanding Doctoral Human Development Project through Co-creation in Different Fields" program (JST SPRING, Japan Grant Number JPMJSP2148.) for their financial support during my doctoral studies.

Chapter 1 Overview of dissertation

Banking plays a pivotal role in the Japanese financial industry, distinguishing itself from the U.S. and Europe (Uchida and Udell, 2019). According to data from the Bank of Japan in 2022, Japanese banks hold 53.59% of financial assets, significantly surpassing the ratios of 20.95% in the U.S. and 42.43% in Europe. Another noteworthy point is the importance of banking for households and companies. For the household sector, 54.2% of financial assets consist of cash and deposits, contrasting with 12.2% in the U.S. and 35.5% in Europe. Regarding corporate liabilities, 25% originates from lending, predominantly provided by banks, in contrast to 6.4% in the U.S. and 26.6% in Europe. These statistics emphasize the indispensable role of banks in the Japanese market, drawing our attention to this crucial financial institution.

Similar to other industries, performance is an important concern in banking-related studies. Previous research has explored the factors influencing bank performance, categorizing them into two main types: internal and external. Internal factors include the capital structure (Berger and Bouwman, 2013, Demirguc-Kunt et al., 2013, Shrieves and Dahl, 1992), ownership structure (Iannotta et al., 2007, Lin and Zhang, 2009, Bonin et al., 2005, Micco et al., 2007), governance (Pathan and Faff, 2013, Adams and Mehran, 2012, Aebi et al., 2012, García-Meca et al., 2015), and diversification (Baele et al., 2007, Stiroh and Rumble, 2006, Laeven and Levine, 2007, Wagner, 2010, Guerry and Wallmeier, 2017). On the other hand, external factors encompass regulation (Barth et al., 2013, Ahamed et al., 2021), competition (Goetz, 2018, Anginer et al., 2014), and the macroeconomic environment (Berger et al., 2000).

This study focuses on the impacts of banks' diversification strategies, which have several meanings, such as lending (loan) diversification, business diversification, and geography diversification. In particular, our emphasis is on business diversification in Japan, as most commercial banks have extended their operations beyond traditional lending, and few Japanese banks have expanded their business abroad (I still refer to geographic diversification in one chapter). Business diversification refers to banks engaging in non-traditional lending businesses. Many studies have shown the increasing diversification in banks' business activities, observed not only in developed countries but also in certain developing markets. The

motivations for banks embracing diversification are multifaceted. One primary consideration is to enhance profitability, particularly during periods of lower interest rates. Bank diversification is also expected to reduce risk, as it allows banks to spread their risk across a variety of assets or products. Furthermore, even if diversification has a limited impact on improving performance, the customer preference for a "one-stop financial supermarket" and competition within the banking sector may drive diversification behavior. However, it raises concerns about whether diversification meets banks' expectations or, in other words, whether diversification improves bank performance.

The answer remains uncertain. Despite a large body of research addressing the impacts of diversification on bank performance, such as profitability, market value, or risk, it is still debatable on this issue. Zouaoui and Zoghlami (2023) review 80 diversification-related studies conducted from 2001 to 2019, and find that diversification effects can be positive, negative, insignificant, or nonlinear. They attribute this to differences in the sample setting (time period and country), variable selection, and estimation method. This implies that the mechanisms behind diversification are complex, so that the net effect is dominated by different channels in different contexts. Three studies have delved into Japanese banks. Sawada (2013) examines the relationship between diversification, market value, and risk in the Japanese banking industry, revealing a positive association between diversification and market value, although the impact on bank risk is not significant. Francis et al. (2018) demonstrate that a more dispersed asset distribution decreases banks' profitability and market value using a sample of Japanese banks from 1989 to 2002. Harimaya and Ozaki (2021) study diversification in Shinkin banks in Japan, a type of non-profit cooperative bank, and find that income diversification can enhance Shinkin banks' efficiency. These studies highlight the inconsistency of results even within a single country. Therefore, to confirm whether diversification benefits exist in Japan, Chapter 2 comprehensively analyzes the relationship between diversification and performance, considering various factors that might influence this relationship.

However, it is insufficient to directly estimate the diversification effect without considering the underlying mechanisms. The estimated diversification effect represents a net effect that may combine both positive and negative influences. As noted by Guerry and Wallmeier (2017), most previous studies have failed to measure components of the net effect, such as economies

of scope and agency problems, which helps to understand the variability in the value of the diversification effect across countries. Therefore, I extend the research from two perspectives by considering two different channels.

The first perspective aims to elucidate the mechanism behind the observed positive diversification effect. When it comes to the mechanisms behind diversification benefits, economies of scope, synergies, and the internal capital market are considered to be effective. Based on the feasibility of the available data and estimation methods, Chapter 3 conducts an estimation of the economies of scope in the Japanese banking industry. Generally, economies of scope refer to the cost-saving effects resulting from joint production. As banks expand their product lines, they can benefit from spreading fixed costs and information sharing, making diversified banks potentially more profitable or valuable. Further, as Japanese banks' outputs have become more diversified, off-balance sheet activities are treated as a new output in the cost function estimation.

The second aims to provide additional evidence from an organizational perspective and consider the effects of governance. Agency costs are often regarded as the primary factor contributing to diversification discounts. As banks expand their businesses, aligning the interests between managers and shareholders becomes more challenging, potentially leading to issues such as empire-building and entrenchment. Moreover, it intensifies conflicts of interest between the headquarters and subsidiaries, or among different divisions or subsidiaries. However, it is hard to quantify agency costs for diversified banks directly since these costs are conceptual in theory but not explicitly reflected in accounting statements. Therefore, I try to estimate the potential effects of agency problems in an indirect way. Specifically, if agency costs significantly impact bank performance in diversified banks, banks with better governance would likely perform better in terms of diversification effects. This is because better governance arrangements can mitigate the adverse effects by enhancing manager monitoring or alleviating interest conflicts. Moreover, In Chapter 4, I turn my focus to the organizational structure of bank groups, and in particular to the subsidiaries under the group, which is commonly referred to as the "bank complexity" issue in prior studies. The reasons for analyzing the impact of the agency costs in the context of bank complexity rather than diversification are that, first, previous studies often treated banking groups as a whole, using non-interest income

ratios to measure bank diversification. However, this approach overlooks the process of how banks expand their business through M&A or the establishment of new subsidiaries. Second, the moderating effects of governance are expected to be more pronounced from an organizational perspective. This is related to the selection of complexity variables. Although there is still no consensus on the metrics of bank complexity in academic research, most studies measure bank complexity from organizational, business, and geographic dimensions. As banks control more subsidiaries spanning various industries and regions, their organizational structure becomes more complex and opaque and, therefore, more likely to have serious agency problems.

On the other hand, unlike the extensive research on diversification, research on bank complexity is relatively limited. With banks becoming more complex in their business, it raises concerns about "too big to fail" or "too complex to fail" since the failure of these complex banks could lead to significant externalities. Particularly after the 2008 financial crisis, regulation on large and complex banks has become a prominent policy issue of global concern. In 2022, several papers in the *Journal of Banking and Finance* investigated the relationship between bank complexity and risk-taking in the United States, Germany, Spain, and Italy. Unfortunately, there is a huge research gap in the Japanese banking industry that needs to be addressed. After the "Japanese Big Bang" financial revolution in 1998, Japanese banks were allowed to expand into non-banking businesses through a holding company structure, which encouraged them to expand into new businesses (e.g., securities and insurance) and regions. This makes Japan a valuable study sample as it introduces more changes to the structure of banks. Moreover, existing studies predominantly focus on the impacts on bank risk, with limited consideration of the effects on banks' market value—a crucial aspect in understanding the motivation for adopting a complexity strategy. Therefore, Chapter 4 conducts an analysis of the impact of complexity on bank market value and risk profile, and the moderating role of bank governance.

The structure of the dissertation and the chapters are summarized below:

Chapter 1 provides an overview of the dissertation, presenting the motivation and some background information for the subsequent studies.

Chapter 2 examines the relationship between bank diversification and performance. I estimate a direct (net) effect of income and asset diversification on banks' profitability and risk. My results show that diversification can improve a bank's ROA but at the cost of declining net interest margins. For bank risk, only asset diversification is found to reduce bank risk. Additionally, I also find that diversification effects vary across different types of banks or non-interest businesses.

Chapter 3 estimates the economies of scope in the Japanese banking industry. Differing from prior studies, I calculate two alternative measures for economies of scope, within-sample scope economies and economies of diversification, at the bank level. The results show that most Japanese banks have exhibited positive economies of scope during the past two decades, with an upward trend in the mean value. Further, I find a negative relationship between bank diversification and economies of scope.

Chapter 4 examines the relationship between bank complexity, governance, and performance. I construct complexity variables based on the number of subsidiaries in terms of organizational, business, and geographic dimensions. Through regression analysis, I estimate the impact of complexity and governance on banks' market value and risk-taking and consider the moderating effects of governance. The results show that only business complexity positively impacts market value, and there is no strong and consistent evidence for a risk-decline effect. While governance is anticipated to mitigate the adverse effects of complexity, empirical findings do not support that. Further, I test three channels that may explain the complexity effects.

Chapter 5 concludes the dissertation and describes the limitations and future works.

Reference

Adams, R. B. and H. Mehran (2012), Bank board structure and performance: Evidence for large bank holding companies, *Journal of Financial Intermediation,* 21**,** 243-67.

Aebi, V., G. Sabato and M. Schmid (2012), Risk management, corporate governance, and bank performance in the financial crisis, *Journal of Banking & Finance,* 36**,** 3213-26.

Ahamed, M. M., S. J. Ho, S. K. Mallick and R. Matousek (2021), Inclusive banking, financial regulation and bank performance: Cross-country evidence, *Journal of Banking & Finance,* 124**,** 106055.

Anginer, D., A. Demirguc-Kunt and M. Zhu (2014), How does competition affect bank systemic risk?, *Journal of Financial Intermediation,* 23**,** 1-26.

Baele, L., O. De Jonghe and R. Vander Vennet (2007), Does the stock market value bank diversification?, *Journal of Banking & Finance,* 31**,** 1999-2023.

Barth, J. R., C. Lin, Y. Ma, J. Seade and F. M. Song (2013), Do bank regulation, supervision and monitoring enhance or impede bank efficiency?, *Journal of Banking & Finance,* 37**,** 2879-92.

Berger, A. N., S. D. Bonime, D. M. Covitz and D. Hancock (2000), Why are bank profits so persistent? The roles of product market competition, informational opacity, and regional/macroeconomic shocks, *Journal of Banking & Finance,* 24**,** 1203-35.

Berger, A. N. and C. H. Bouwman (2013), How does capital affect bank performance during financial crises?, *Journal of Financial Economics,* 109**,** 146-76.

Bonin, J. P., I. Hasan and P. Wachtel (2005), Bank performance, efficiency and ownership in transition countries, *Journal of Banking & Finance,* 29**,** 31-53.

Demirguc‐Kunt, A., E. Detragiache and O. Merrouche (2013), Bank capital: Lessons from the financial crisis, *Journal of Money, Credit and Banking,* 45**,** 1147-64.

Francis, B. B., I. Hasan, A. M. Küllü and M. Zhou (2018), Should banks diversify or focus? Know thyself: The role of abilities, *Economic Systems,* 42**,** 106-18.

García-Meca, E., I.-M. García-Sánchez and J. Martínez-Ferrero (2015), Board diversity and its effects on bank performance: An international analysis, *Journal of Banking & Finance,* 53**,** 202-14.

Goetz, M. R. (2018), Competition and bank stability, *Journal of Financial Intermediation,* 35**,** 57-69.

Guerry, N. and M. Wallmeier (2017), Valuation of diversified banks: New evidence, *Journal of Banking & Finance,* 80**,** 203-14.

Harimaya, K. and Y. Ozaki (2021), Effects of diversification on bank efficiency: Evidence from Shinkin banks in Japan, *International Review of Economics & Finance,* 71**,** 700-17.

Iannotta, G., G. Nocera and A. Sironi (2007), Ownership structure, risk and performance in the European banking industry, *Journal of Banking & Finance,* 31**,** 2127-49.

Laeven, L. and R. Levine (2007), Is There a Diversification Discount in Financial Conglomerates, *Journal of Financial Economics,* 85**,** 331-67.

Lin, X. and Y. Zhang (2009), Bank ownership reform and bank performance in China, *Journal of Banking & Finance,* 33**,** 20-29.

Micco, A., U. Panizza and M. Yanez (2007), Bank ownership and performance. Does politics matter?, *Journal of Banking & Finance,* 31**,** 219-41.

Pathan, S. and R. Faff (2013), Does board structure in banks really affect their performance?, *Journal of Banking & Finance,* 37**,** 1573-89.

Sawada, M. (2013), How does the stock market value bank diversification? Empirical evidence from Japanese banks, *Pacific-Basin Finance Journal,* 25**,** 40-61.

Shrieves, R. E. and D. Dahl (1992), The relationship between risk and capital in commercial banks, *Journal of Banking & Finance,* 16**,** 439-57.

Stiroh, K. J. and A. S. Rumble (2006), The Dark Side of Diversification: The Case of US Financial Holding Companies, *Journal of Banking and Finance,* 30**,** 2131-61.

Uchida, H. and G. F. Udell (2019), Banking in Japan: A Post-global Financial Crisis Perspective. in: Berger, A. N., P. Molyneux and J. O. S. Wilson (eds.) The Oxford handbook of banking. Oxford University Press.

Wagner, W. (2010), Diversification at financial institutions and systemic crises, *Journal of Financial Intermediation,* 19**,** 373-86.

Zouaoui, H. and F. Zoghlami (2023), What do we know about the impact of income diversification on bank performance? A systematic literature review, *Journal of Banking Regulation,* 24**,** 286-309.

Chapter 2 Bank diversification and performance: Evidence from Japan

Abstract: This paper examines the relationship between bank diversification and performance in the Japanese banking sector. I use panel data from 141 banks over the period 2000-2022 to investigate whether banks can improve profitability and reduce risk through diversification strategies. Our evidence shows that diversification can improve bank profitability at the cost of a decline in net interest margins, suggesting banks are using the interest business as a loss leader to promote other business lines. We find that asset diversification has a risk-reducing effect, which supports the portfolio hypothesis. Some evidence implies that there is a more complex nonlinear relationship. This can be partly attributed to bank type, as the diversification effects vary across different types of banks. Furthermore, the decomposition of non-interest income reveals that fees and commissions negatively influence ROA while simultaneously reducing bank risk.

Keywords: bank diversification; profitability; bank risk; Japanese banks

2.1. Introduction

Whether diversification in the banking industry will influence bank performance, such as profitability or risk-taking, is always a hot topic. Unlike other industries, banks in most economies are highly regulated because of their inherent high-leverage capital structure and concerns about financial stability. One of the implements is the banking operation restrictions, meaning banks are prohibited from engaging in particular fields or transactions. Especially after the 2008 financial crisis, authorities began to reconsider reasonable business scope for banks, as some studies attributed the crisis to accelerated deregulation and regulatory arbitrage in the banking sector (Acharya and Richardson, 2009, Crotty, 2009, Bhidé, 2011). For example, the U.S. government accepted the Volcker Rule[1] in 2010, prohibiting banks from engaging in short-term proprietary trading with their own accounts. However, the scope of banks has expanded compared to the past through financial deregulation and innovation (DeYoung and Torna, 2013).

Though traditional bank theory tells us that the critical business of commercial banks is to make loans, the increase in non-lending activities has become an obvious trend in many countries. Banks have a net cost advantage in connecting with depositors and borrowers (Diamond, 1984), and therefore, interest rate differential naturally becomes the most important profit source for commercial banks. Nevertheless, DeYoung and Rice (2004a) show that non-interest income in the U.S. banking sector has experienced rapid growth since the early 1980s. The share of non-interest income doubled from 20% in 1970 to 40% in 2003. Data from the Federal Reserve Bank of New York in Q1 of 2023 indicates that the non-interest income ratio has remained relatively stable since 2010, consistently above 40 percent. Sawada (2013) also finds a similar tendency in the Japanese banking industry, a steady growth compared with the early 21st century. While both banks in Japan and the U.S. have been prohibited from engaging in nonbank activities for a long time, like underwriting or insurance sales, banks in Europe, where there are few limitations in banking business operations, experienced a similar increase

[1] It is named after Paul Volcker, the former United States Federal Reserve Chairman. The Volcker Rule refers to section 619 of the Dodd-Frank Wall Street Reform and Consumer Protection Act.

in non-interest income. Köhler (2015) shows that without strict business regulation, the revenue from non-interest income activities across 15 European countries has risen from 36% to 40% (commercial banks, 2000-2011). Even some emerging economies, such as China (Berger et al., 2010), India (Ahamed, 2017), and Latin America (Wu et al., 2020), have witnessed a shift toward non-interest income activities. In a word, it is clear that more and more banks are expanding their non-lending operations.

The reasons why banks choose to be more diversified are mixed. Firstly, firms or shareholders can benefit from it. Though it is still an open question whether bank diversification is value-creating, some empirical research has revealed a positive correlation between diversification and bank performance (Elsas et al., 2010, Filson and Olfati, 2014, Baele et al., 2007). Banks with a higher share of non-interest income are found to have a diversification premium. The increase in stock returns or profits will certainly alter management decisions on diversification decisions. Secondly, banks can take full advantage of existing resources for non-lending financial activities. Generally, banks are considered information producers in financial markets. There are no obvious industry barriers for banks to participate in other relevant financial businesses due to the homogeneity of financial products. Moreover, banks often have a close relationship with their customers, providing a golden opportunity to offer more services, like a one-stop financial supermarket. Besides, irrational management also contributes to an overvalued diversification level (Aggarwal and Samwick, 2003). Because of information asymmetry, managers who pursue personal interests, such as a better future career or enjoy power, will more likely adopt a diversification strategy.

There are plenty of studies regarding the effect of bank diversification in developed and emerging markets, but it remains controversial. Zouaoui and Zoghlami (2023) conduct a systematic literature review of 80 papers from 2000 to 2019 and find that the empirical results are mixed. They conclude that differences in study periods, regions, variable selection, and estimation methods may produce different results. For example, most studies focusing on the U.S. banking industry find that engaging more in non-traditional businesses would have a negative effect on banks' market performance (Laeven and Levine, 2007), risk-adjust profit

(Stiroh, 2004, Stiroh and Rumble, 2006), technical efficiency (Elyasiani and Wang, 2012), and bank risk-taking (Shim, 2013). In contrast, Elsas et al. (2010) examine banks in nine countries (U.S. and EU) from 1996 to 2008 and find that diversification is positively linked with bank profitability and market valuations, which is strongly against diversification discount. Sanya and Wolfe (2011) use a large sample, including 226 listed banks from 11 emerging economies, and the results indicate that banks with a higher diversification level exhibit higher risk-adjusted profits and a lower insolvency risk. Some studies also suggest that bank type can influence the relationship between diversification and performance (see more in Mercieca et al., 2007, Lepetit et al., 2008a). The mixed evidence suggests that the mechanisms of bank diversification are complex, and the effective channels may differ due to disparities in banking regulations and the macroeconomic environment.

While many empirical studies have addressed the issue of bank diversification, there needs to be more focus on the Japanese banking sector. Japan is a well-developed country with a high share of indirect finance and a unique banking business environment. For example, there was a long period of economic depression in Japan called “the lost 30 years”. The Bank of Japan (the central bank in Japan) adopted the zero-interest-rate policy in 1999 to deal with the deflation. This led to a decline in interest rates on deposits and loans, posing a challenge for Japanese banks in generating profits from their traditional lending businesses. In addition, while banks are now allowed to enter other financial sectors through a holding company structure, the share of Bank Holding Companies(BHCs) is still much lower than that in the U.S.[2], suggesting a different management strategy between the two countries. All these factors may lead to different diversification effects in the Japanese banking sector than in other countries. This paper is also motivated by contrasting empirical findings concerning the impact of bank diversification on Tobin's Q found in Japan. Sawada (2013) finds a positive relationship between diversification and Tobin’s Q using a sample of 991 bank-year observations from 1999 to 2011. In contrast, a cross-country study conducted by Guerry and Wallmeier (2017) suggests that the marginal effect of bank diversification on Tobin's Q is negative. These divergent results

[2] According to Avraham et al. (2012), BHCs hold nearly all U.S. banking sector assets.

may be attributed to differences in model specifications, sample selection, or other factors, emphasizing the need for more empirical evidence on bank diversification based on the Japanese banking sector.

This paper focuses on Japanese commercial banks and comprehensively examines the impact of diversification on performance as measured by profitability and risk. In evaluating profitability, an additional metric, net interest margin (NIM), is used alongside ROA to assess whether banks utilize loan operations as a loss leader to promote their non-interest businesses. I consider two types of bank risk: the volatility of profitability and the insolvency risk measured by Z-score. Although these indicators are widely employed in prior literature, to the best of my knowledge, few studies have used them in Japan, which provides additional evidence for the findings in Sawada (2013). As for bank diversification, I follow the concepts of Laeven and Levine (2007), which measure diversification from income and asset perspectives. The comparison between the two metrics can help us to understand different aspects of bank diversification. I also test possible nonlinear relationships by introducing the quadratic terms for diversification variables. The sample includes 141 commercial banks in Japan from 2000 to 2022. Unlike other studies in Japan, this study includes new forms banks, such as online banks, and estimates the marginal effects of different types of banks as bank type may affect diversification effects. Additionally, I explore which kind of non-interest businesses contribute the most to the net effects by decomposing bank revenue into four components. Furthermore, I investigate whether diversified banks performed better or worse during the crisis periods. To do so, I reevaluate the relationship between diversification and performance using data from the 2008 financial crisis and the COVID-19 pandemic.

The main finding is that diversification can improve banks' ROA at the cost of decreasing net interest margins, and a risk-decline effect only exists for asset diversification. The empirical results show a positive association with ROA, alongside a negative correlation with net interest margins. This suggests that banks adopt the strategy of underpricing credit facilities as a loss leader to bolster other revenue streams. I find that banks with higher asset diversification have lower income volatility and insolvency risk, while it turns out to be insignificant for income

diversification. This discrepancy in results may be attributed to differences in measuring different aspects of the bank's activities. At the same time, the result highlights a non-linear relationship between diversification and ROA. Diversified banks tend to be more profitable, but the positive marginal effects on ROA gradually diminish as banks become more diversified. To elucidate the non-linear relationship, I consider the effect of bank types, as different types of banks do not have the same distribution in terms of diversification. The diversification effects are found to vary across different banks. In particular, second regional banks that are highly dependent on traditional lending businesses have higher positive marginal effects than other banks. Nevertheless, the non-linear relationship remains evident even when we focus our estimation solely on regional banks, suggesting that the combined effects of diversification benefits and costs are variable, as noted by Guerry and Wallmeier (2017).

In the decomposition analysis of the non-interest income ratio, I find that fee income has a negative impact on ROA, while trading and other income can increase ROA. This may be due to the finding that fee income has a more significant negative impact on net interest margins. However, banks with high fee income ratios enjoy the advantage of having a lower risk of bankruptcy. Finally, findings on the crisis period indicate an opposite diversification effect for income and asset diversification. Specifically, during these turbulent periods, banks diversified in assets are less risky, while banks diversified in income exhibit a higher risk.

This paper contributes to the existing literature in four aspects. First, it provides new evidence of bank diversification in the Japanese banking sector. Few previous studies have shed light on Japanese banks except for Sawada (2013). Compared to Sawada (2013), this paper examines the diversification effects over a longer sample period and includes a larger number of Japanese banks, especially online banks that have emerged in recent years. In addition, asset diversification variables are also used to measure different aspects of bank diversification. Second, this paper suggests a possible nonlinear relationship between diversification and performance, generating new insights into understanding diversification effects. The results show that banks that are less diversified in their revenue have a more pronounced positive effect on ROA compared to highly diversified banks. Further analysis of the impact of bank

types also shows that diversification effects vary across different types of banks, which provides new empirical evidence to understand bank behavior. Third, this study employs different metrics to evaluate overall profitability and the profitability of traditional businesses. ROA or ROE is usually used as a measure of profitability, and few studies have explored the impact of diversification on both ROA and NIM (Zouaoui and Zoghlami, 2023). Prior studies have demonstrated a negative relationship between diversification and NIM (see more in Maudos and Solís, 2009, Nguyen, 2012). This study reconfirms the existence of such a negative relationship and provides evidence that diversification can improve ROA. This implies that despite the adverse impact of diversification on intermediation margins, its overall effect on profitability is positive. Finally, I consider the individual impact of non-interest businesses, such as fee and trading operations, to offer a more comprehensive understanding of how different revenue sources influence bank performance.

This paper is structured as follows. In section 2, I will introduce some basic information about the Japanese banking sector. In section 3, I present the previous literature about bank diversification, including both theoretical and empirical research. Section 4 shows the data, variables, and methodology used in the empirical analysis, and section 5 presents the main results for bank diversification and the robustness tests. In section 6, three additional analyses are performed. Section 7 concludes.

2.2. Understanding the background of bank diversification in Japan

2.2.1 The segmentation of Japanese banking sector

According to the 1981 banking law, a bank in Japan can be defined as "a person who operates banking business under the license of the Prime Minister[3]." The banking business refers to lending, deposit-taking, and exchange business. The Japanese banking sector can be divided into city banks, regional banks, second regional banks, trust banks, new forms banks, Shikin bank and credit cooperatives, and other banking service providers.

[3] See the 1981 Banking Act, article 2.

City banks (mega banks) are a type of ordinary bank[4] and refer to the large banks in Japan. There are now only four city banks after the banking merge wave in the early 2000s (MUFG Bank, Mizuho Bank, Resona Bank[5], and Sumitomo Mitsui Banking Corporation). Regional banks and second regional banks are regionally focused, while second regional banks are usually much smaller than regional banks. Trust banks are specially authorized banks that can offer ordinary commercial bank services and trust services. Most of the new forms banks are newly established online banks and those that cannot be categorized as the types above. Online banks often have the following characteristics: no branch, related to non-financial companies, and online service-based.

According to Uchida and Udell (2014), Shikin banks and credit cooperatives aim to provide banking services only to member SMEs and individuals. Still, they have been permitted to offer some special services to nonmembers since the 1980s. In addition, it is worth noting that neither of them is a legally commercial bank because they are non-profit legal corporations, and their operations are restricted to a certain area under special laws.

2.2.2 The decrease in interest spread

To understand why banks in Japan choose to become more diversified, the decrease in interest spread might give some hints. As a part of financial deregulation, Japan started the Market-Oriented Interest Rate Reform and completed it in 1994. Meanwhile, both deposit and lending rates fell sharply. The 1997 Asian financial crisis brought more uncertainty to Japan's economic recovery. To deal with the recession, the Bank of Japan started the "zero-interest-rate policy" in 1999. In addition, a series of quantitative easing policies have also been introduced. Because of those long-term loose monetary policies, Japan has entered an era of low interest rates.

Figure 2-1 shows the decline in banks' interest income. Despite a slight rebound during the 2007-2008 global financial crisis, there has been a clear downward trend in deposit and loan

[4] A special item used in Japan to distinguish the specialized banks before World War II. Now it can simply understood as the commercial bank. Generally,trust bank and state-owned bank are not ordinary bank.
[5] Saitama Resona Bank also can be called city bank due to its special ownership relationship with Resona Bank, but it is not considered the traditional city bank in this paper.

yields starting in 1997. The interest spread measures the gap between yields on loans and deposits, which shows the net return from traditional lending activities. The decline in lending and deposit interest rates did not worsen the bank's interest income until 2005. The interest spread began to decline in 2007 and fall to half of the 2007 level by 2022. This could explain why banks have to turn to potential high-profit noninterest activities to maintain or exceed the past profits level.

2.2.3 Deregulation and competition from other industries

Similar to the U.S., banks in Japan were also prohibited from engaging in other financial businesses after World War II. To rebuild and effectively manage the financial industry, the authorities formulated strict regulations to distinguish financial institutions with different functions. It was not until the 1980s that Japan began to advance financial liberalization and internationalization reforms. With the promulgation of the 1981 Banking Law, banks can operate ancillary businesses, such as debt guarantees, security trading, and other noninterest activities. It helped banks change the traditional management perspective that emphasizes the balance of loans and deposits (Nezu, 1999). Furthermore, as a part of the so-called Japanese Big Bang, it has become possible to establish a financial holding company since March 1998. Banks can enter other financial businesses, such as investment banking, insurance, etc., through a holding company structure. Not only have the big four city banks transformed into BHCs, but the number of BHCs is increasing.

In addition to the deregulation, traditional banks face competition from other industries since non-financial companies are allowed to set up bank subsidiaries. For example, Seven & i Holdings, the leading enterprise in the retail industry, established the Seven Bank in 2001. According to the Bank of Japan, there were only four new forms banks in 2005, but the number became 14 in 2023. The increase in competitors may seize traditional banks' market and encourage them to provide diversified services to meet different needs. Compared to traditional banks, new forms banks have several competitive advantages in terms of (1) lower operation costs: most new forms banks, like online banks, don't need to hold heavy fixed assets or can utilize the resources from parent companies or partners, allowing them to offer a little higher

deposit rate and charge less in transaction fee to attract customers; (2) synergy effects with the parent company, particularly among FinTech and commercial companies. For example, AEON is a giant in the Japanese retail market. As its subsidiary, the branches of AEON bank are almost set up in the group's shopping malls and near the supermarket. Moreover, the customers will enjoy a higher discount in AEON's stores if they hold a card issued by AEON bank. This example shows how synergy can arise between banks and other group members.

2.3. Literature review

2.3.1 Profitability, firm value, and bank diversification

According to traditional corporate finance theory, as for-profit corporations, banks are more engaged in non-interest activities to maximize bank value or shareholder value. Elsas et al. (2010) argue that diversification is value-creating because banks can enjoy economies of scope and synergy effects. Because of a broader share of infrastructure, human capital, information, and technologies development among the group, diversification is thought to be cost-saving and thus can improve bank profitability. Zhang and Malikov (2022) find significant economies of scope in the U.S. banking industry, which suggests that banks can save costs through the joint production of loans, securities, and banks' off-balance sheet activities. Vennet (2002) shows that conglomerates and universal banks are more efficient in cost and revenue than other banks in the EU. However, some studies also report diseconomies of scope or insignificant results (see more in Berger et al., 1987, Clark, 1988, Abedifar et al., 2018).

Other benefits arise from stronger monitoring from headquarters and efficient resource allocation through the internal capital markets (Stein, 1997). However, whether diversification is value-creating or destructing also depends on the costs associated with diversification. Agency costs (Jensen and Meckling, 1976) are a noticeable cost mentioned in most studies, which arise from the conflicts between insiders and outsiders, headquarters and divisions or subsidiaries. As managers' interest does not always align with shareholders, they may pursue private benefits at the expense of corporate value. Moreover, with the increasing bank

diversification, the business scope and organization structure tend to be more complex, making monitoring more challenging and exacerbating conflicts of interest. Aggarwal and Samwick (2003) develop a contracting model to analyze why managers try to diversify firms. They find that managers have a stronger incentive to diversify firms if they have gotten private benefits from diversification. In addition, inefficient investment and resource misallocation due to interest conflicts between divisions (Harris et al., 1982, Rajan et al., 2000, Stulz, 1990, Jensen, 1986) are also the dark side of diversification.

Consistent with the above possible channel analysis, the impact of bank diversification remains controversial. On the one hand, many researchers find that, like other non-financial industries, diversification discounts exist in the banking sector. DeYoung and Rice (2004b) find that increases in banks' non-interest income share in the U.S. are negatively linked with risk-adjusted ROE from 1989 to 2001. Stiroh (2004) finds similar results on a broader period of 1979-2000, noting that trading revenue is the most significant contributor to the decline in risk-adjusted profits. Stiroh and Rumble (2006) then focus on U.S. bank holding companies, which allow a wider range of operations in non-interest activities. The results show that increased non-interest income is associated with a lower risk-adjust ROA(ROE) because the increasing exposure to higher-risk non-interest activities offsets diversification benefits. Schmid and Walter (2009) examine the financial conglomerates, including investment banks, commercial banks, insurance companies, and asset management in the U.S., and conclude a conglomerate discount among financial intermediaries. In addition to the U.S. market, Mercieca et al. (2007) examine small European banks from 1997-2003, and the result shows a similar negative relation. Berger et al. (2010) find that asset diversification is associated with lower profits and higher costs in China from 1996-2006. Moreover, a recent study by Guerry and Wallmeier (2017) also supports a negative relationship between diversification and bank value before the 2008 financial crisis.

On the other hand, some studies also verified a positive relationship between bank diversification and performance. Baele et al. (2007) examine 255 banks in 17 European countries from 1989-2004 and find the long-run performance measured by noise-adjusted

Tobin's Q is positively linked with non-interest income share. Sanya and Wolfe (2011) show a positive relationship between risk-adjusted returns and diversification using a bank sample from 11 emerging countries. In addition, another global research, including 1334 banks from 101 countries, made by Demirgüç-Kunt and Huizinga (2010) shows a nonlinear relation. Their results imply an inverted U-shape relation, where diversification benefits are significantly positive when the diversification level is low. It's important to note that most studies that find positive relations are based on non-US markets, suggesting a complex mechanism in this issue.

2.3.2 Risk and bank diversification

Portfolio theory suggests that the portfolio of different investments that are not perfectly correlated can achieve the same expected return with a lower risk. This may explain why banks expanding into other non-interest activities can reduce risk. Banks can offer imperfectly correlated products or services to build a diversified revenue portfolio, which helps banks maintain a stable revenue and reduce bankruptcy risk. All idiosyncratic risks can be well-diversified in an ideal situation, and banks only hold systemic risks.

However, most empirical studies contradict the notion that diversified banks are less risky. Stiroh and Rumble (2006) find that an increased reliance on non-interest income is associated with more volatile profits in the U.S. banking sector. A similar relationship is also confirmed in other countries. Lepetit et al. (2008a) examine European banks for 1996–2002 and find banks that have expanded into non-interest activities tend to have higher earnings volatility and insolvency risk than those focused on traditional banking activities. A more recent study conducted by Williams (2016) also confirms that banks in Australia with less non-interest income share and higher revenue concentration have a more stable profitability. Moreover, much evidence has addressed that non-interest activities are riskier but not necessarily more profitable than lending (see e.g. Stiroh and Rumble, 2006, DeYoung and Roland, 2001, De Jonghe, 2010, Demirgüç-Kunt and Huizinga, 2010, Brunnermeier et al., 2020). This may be attributed to the fact that fee-based revenues have a less stable relationship with customers, higher operating leverage, and few capital requirements on non-interest income activities (DeYoung and Roland, 2001).

Another finding is that bank diversification will increase systemic risk. Allen and Jagtiani (2000) find that BHCs expanding in securities underwriting and insurance would result in greater systematic and systemic risk due to the increasing convergence in business across financial firms. This view is confirmed by Wagner (2010). He uses a two-bank model to explain why financial institutions becoming more similar due to diversification raises the probability of a systemic crisis. De Jonghe (2010) studies the bank's systemic risk measured by tail betas under extreme economic conditions and finds that the non-interest activities increase tail betas. Brunnermeier et al. (2020) obtain similar results on systemic risk, especially for tail risk and interconnectedness risk, and also find interest-generating activities can reduce systemic risk. Their results suggest that diversified banks do not contribute as much to the financial system's stability as specialized banks.

Nonetheless, some studies endorse the idea that diversification can mitigate risk. Baele et al. (2007) find a non-linear and downward-sloping dominated relation between non-interest income and idiosyncratic risk. It implies that banks can mitigate bank-specific risks through diversification, which is evidence of the portfolio theory. DeYoung and Torna (2013) study cases of bank failures in the United States during the financial crisis and find some fee-based activities, such as securities brokerage and insurance sales, would reduce the probability of bank failure. Köhler (2015) examines banks in 15 EU countries from 2002 to 2011 and finds that retail-oriented banks will become more stable if they increase the share of non-interest income. But he also addresses that diversification effects on risk vary with bank business model, and researchers should distinguish banks when analyzing this issue.

In conclusion, the studies mentioned above have shown contradictory facts that there is no consensus on the diversification effect. As discussed by Zouaoui and Zoghlami (2023), differences in the measure of diversification and performance, models, regions, and data periods lead to different results. This makes it difficult to determine which results are more plausible. Therefore, to minimize the influence of factors that could potentially impact the diversification effect, I focus on a single market and use a 23-year-long sample to estimate the diversification effect for different types of banks.

2.4. Data and methodology

2.4.1 Data

There are five types of commercial banks in Japan: city bank, regional bank, second regional bank, trust bank, new forms bank. However, trust banks are excluded from the sample due to legal limitations on the trust business. Banks are only allowed to operate trust businesses if they obtain a license from the Financial Services Agency. Therefore, trust banks usually have a sizeable non-interest income from trust operations, while other banks cannot compete with them due to legal limitations. In contrast, even though some new forms banks concentrate on fee-based activities and thus have a higher non-interest income ratio, there are no restrictions on their interest business. In addition, this paper aims to include a larger number of Japanese banks, while the consolidated data are not provided if a bank becomes a subsidiary of a BHC. Therefore, I use non-consolidated accounting data for banks and exclude BHCs from the sample to avoid duplication problems. Foreign banks or foreign bank branches are also excluded from this study. Finally, I drop the observations for the first three years of newly established new forms banks, as they typically do not generate interest income immediately, and initial returns may not accurately represent their actual profitability. The distribution of different types of banks is reported in Table 2-1. It illustrates that while regional and second regional banks hold substantial proportions at 54.18% and 36.15%, the importance of new forms of banks should not be overlooked.

The sample consists of unbalanced panel data, including 2689 bank-year observations of 141 banks for 2000–2022. I chose a 23-year sample period because Japan has gradually deregulated financial institutions since 1999, and this sample period is sufficient to reflect the trend of bank diversification in Japan. The sample covers nearly all commercial banks in Japan, no matter whether they were merged or liquidated during the past 23-year period. In particular, the merged bank is treated as a new bank with a different ID. I obtain most of the data from the Nikkei NEEDS-Financial Quest database, a famous data provider in Japan, and manually fill in the missing data through annual reports.

2.4.2 Methodology

In order to investigate the link between bank diversification and profitability, a two-way fixed effects model is employed in this paper. I estimate the following specification for bank performance:

$$Performance_{it} = \alpha + \beta Diversification_{it} + \gamma Control_{it} + \mu_i + \theta_t + \varepsilon_{it} \qquad (1)$$

where i is the bank identifier, and t denotes time. $Performance_{it}$ is a measure of profitability and bank risk. $Diversification_{it}$ is the degree to which banks engage in non-traditional operations, including both income and asset-based diversifications. In addition, the quadratic term of diversification variables will also be introduced, as there might be a U-shaped relationship. $Control_{it}$ is a vector of control variables that measures bank characteristics that may affect bank profitability or risk. μ_i and θ_t denote individual and year-fixed effects. The fixed effects can capture part of residuals that do not change over time in a cross-sectional regression. Therefore, the fixed effects model is often employed to alleviate the endogenous problems caused by omitted variables. Finally, the fixed effects regressions are justified using the Hausman Test and have robust standard errors clustered at the bank level.

2.4.3 Variables

In the following, I describe the main variables in the regressions. Table 2-2 summarizes the definitions and calculations of these variables in detail. It is necessary to note that all continuous variables are winsorized at 1% and 99% to exclude the effect of extreme values.

2.4.3.1 Performance

Generally speaking, there are two different ways to measure bank performance: accounting-based or market-based performance. However, because banks under the umbrella of BHCs have to be delisted, there is no longer market-based data for these banks. Therefore, using accounting data to measure bank performance is a better choice.

As theories suggest that diversification effects may work through economies of scope, bank

profitability can be used to proxy performance. Like many previous studies, I use return on assets (ROA) and net interest margin (NIM) to measure bank profitability. Compared to ROA, NIM measures the profit from interest activities and can be used to test whether banks utilize loans as a loss leader product to promote non-interest products, as argued in Valverde and Fernández (2007) and Lepetit et al. (2008b). In terms of risk, this study employs the standard deviation of ROA and Z-score as the dependent variable. The standard deviation of ROA is calculated based on a past three-year rolling time window[6]. Z-score is an indicator of insolvency risk and can be calculated by

$$\text{zscore} = \frac{\text{ROA} + \text{CAR}}{\sigma_{\text{ROA}}} \tag{2}$$

where CAR is the equity to assets ratio (E/A) and σ_{ROA} is the standard deviation of ROA. According to Laeven and Levine (2009), Z-score measures the distance to default where shareholder equity is insufficient to compensate for the current loss. A higher Z-score indicates a lower possibility of insolvency, and thus the bank is more stable. Moreover, I use the natural logarithm of the Z-score because the Z-score is not normally distributed but highly skewed. While the Z-score is expected to be positive, the sample contains several negative observations, especially during the 2008 financial crisis. These banks incurred a huge loss during the crisis but were prevented from entering bankruptcy through financial aid from their parent company or the government. However, it is not wise to directly drop the negative, as it would result in the loss of crucial information highlighting the underperformance of these banks. One solution is to winsorize the Z-score, similar to other variables, and these negative values will be replaced by the positive value at 1% quantile.

[6] There is a trade-off between the selection of the rolling window and sample size since ROA is calculated at the year level. For robustness, I also calculate the standard deviation of ROA over a 5-year rolling window to measure the long-term volatility of profitability. The signs of key variables remain unchanged, while some coefficients become statistically insignificant when the dependent variable is insolvency risk.

2.4.3.2 Diversification

In this paper, I concentrate on product diversification, which means banks expand their business beyond traditional lending activities to offer new products or services. In most studies, bank activities are usually divided into interest and non-interest activities. Interest activities are all interest-generated activities, such as common lending or inter-bank lending. The rest are collectively referred to as non-interest activities, such as fee-based activities and derivatives trading.

According to Laeven and Levine (2007), there are two different methods to measure diversification: income-based and asset-based. As for income diversification, the income statement shows how banks make profits and enables us to distinguish income streams from various operations in detail. In general, banks' operation income (also called ordinary income) in Japan can be divided into five parts: interest, fees and commissions, trading, other income[7], and trust fees. Though the trust fee is listed as an independent item, it can be recorded as fees and commissions since it is also a fee-based service. Therefore, the ratio of non-interest income to total ordinary income (noninterestratio), a most widely used indicator, can be used to measure the extent to which banks engage in non-interest operations. A bank with a lower non-interest income ratio indicates that it mainly relies on interest-generating activities and may be considered a more traditional bank. It is necessary to note that I use gross income rather than net income to calculate the non-interest ratio because the net income on fee-generating or trading activities becomes negative within a certain number of years. Asset diversification is based on the bank balance sheet that pictures the asset structure of a given bank. Instead of total assets, the earning assets are used as the denominator. Earning assets refer to those that can generate revenue, including loans, securities, investments, and other earning assets in a Japanese bank's balance sheets. Thus, the share of non-loan assets(nonloanasset) measures how banks allocate assets between lending and other activities. A higher ratio of non-loan assets indicates that the bank is less specialized in loan-making and possibly more diversified.

A critical difference between income and asset diversification is that the latter is calculated

[7] Following Sawada(2013), "gain on sale of equity securities" is accounted as trading income.

from the "stock" variables rather than the "flow" variables in income diversification. Therefore, it is more proper to consider a lagged asset diversification effect on bank performance because changes in current asset allocation are unlikely to result in immediate gains. Unfortunately, both asset and income diversification variables suffer from measurement problems. The asset-based variable is underestimated since off-balance sheet activities connected with non-traditional activities are neglected (Guerry and Wallmeier, 2017). On the other hand, Laeven and Levine (2007) point out that the non-interest income ratio overestimates the degree of diversification because loans can also yield fee income. To alleviate the measurement problems, I introduce another income-based variable based on the traditional bank business of lending and exchanges in the robustness test. Overall, there is no definite answer to which metric is better. I will show the results of asset and income-based measures, which can help us understand diversification from multiple perspectives.

In addition, the Herfindahl-Hirschman Index (HHI) is widely used to measure bank diversification because it indicates the concentration of income or asset portfolios. I follow the method proposed by Elsas et al. (2010), and income-based HHI is calculated as

$$incomeHHI = 1 - \Sigma_{i \in I} \left(\frac{income_i}{\Sigma_{i \in I} income_i} \right)^2 \quad (3)$$

where $income_i$ refers to four different sources of income: interest, fees and commissions, trading, and other income. The advantage of HHI is that it can distinguish banks with a larger share of non-interest income. These banks specialized in a single operation are lower in HHI, while banks with equally distributed income sources are considered the most diversified. Therefore, a higher HHI signals that the bank is more diversified.

Laeven and Levine (2007) propose a measure similar to HHI to calculate the dispersion between interest and non-interest income or loans and other earning assets. However, it can only be used to calculate asset diversification due to the prerequisites of binary classification. The asset diversification is calculated as

$$assetdiversity = 1 - \frac{|loans - other\ earning\ assets|}{total\ earning\ assets} \quad (4)$$

Assetdiversity measures the relative size between loans and other earning assets. It takes a value between 0 and 1, and increases as the non-loan assets ratio gets closer to 0.5. Although a 50/50 ratio is not necessarily optimal in asset allocation, it is a natural choice when the parameters between return and risk are uncertain (Guerry and Wallmeier, 2017). Therefore, a higher value of **assetdiversity** indicates greater diversification. I do not calculate a Herfindahl-Hirschman Index for asset diversification because it is a linear combination of the non-loan assets ratio and its quadratic term. Thus, introducing the quadratic term of the non-loan assets ratio into the regression would yield the same results.

2.4.3.3 Control variable

To control for the influence of other factors, I introduce several control variables based on classic theories and previous empirical studies: (1) the natural logarithm of total assets, which is considered to be correlated with profitability due to the economy of scale (Benston et al., 1982, McAllister and McManus, 1993); (2) capital ratio, which measures the capital structure of banks and has an influence not only on risk-taking (Shrieves and Dahl, 1992) but also on bank value (Demirguc-Kunt et al., 2013) and lending activities (Carlson et al., 2013, Gambacorta and Mistrulli, 2004); (3) overhead ratio(OHR) and fund cost. These two variables measure cost-efficiency in banking management. Banks with a lower overhead ratio or fund cost are considered more efficient in cost management and thus are expected to perform better; (4) asset growth rate. A higher asset growth rate may indicate a promising growth potential as banks are expected to generate greater profits from the expansion (Laeven and Levine, 2007); (5) non-performing loan ratio. Many empirical studies have confirmed that non-performing loan ratios negatively affect bank performance (García-Herrero et al., 2009, Berger and DeYoung, 1997, Goetz et al., 2016, Brunnermeier et al., 2020); (6) a dummy variable of BHCs. Banks affiliated with BHC may be more profit-efficiency (Yamori et al., 2003) and have a lower financial distress risk (Ashcraft, 2008) than independent banks. Finally, I also use year-

fixed effects to control the macro-environmental characteristics.

2.4.3.4 Summary statistics

Table 2-3 presents the summary statistics of the regression variables. Due to a highly leveraged business model, banks have a much lower ROA than other industries. The mean value of ROA in the sample is 0.001, and the volatility of ROA, as measured by the standard deviation of ROA, is also small, with a mean value of 0.02, implying that the profitability of Japanese banks is relatively stable. As to the core independent variables, though the difference between the maximum and minimum value of the non-interest income ratio is significant, the mean value (0.255) is lower than in other countries, as shown by Guerry and Wallmeier (2017)[8]. It may imply that most Japanese banks still rely on interest-generating income.

Table 2-4 shows the correlations between independent and control variables. The income diversification measures, **noninterestratio** and **incomeHHI**, are positively correlated with a correlation coefficient of over 0.8. This is due to the fact that most of the banks in the sample are traditional commercial banks with a relatively high share of interest income. In contrast, the correlation coefficient between asset diversification measures is smaller, implying a significant difference in the earning asset structure of different banks. Although income and asset variables measure bank diversification from different perspectives, they are positively correlated. For other control variables, the correlation coefficients are all smaller than 0.7, a threshold of correlation coefficients proposed by Dormann et al. (2013). Thus, they can be considered appropriate controls to alleviate the collinearity problem.

2.5. Empirical results

2.5.1 Profitability and bank diversification

In this section, I first examine the relationship between bank profitability and diversification. Table 2-5 presents the results on Eq-1 when ROA and NIM are regressed as the dependent

[8] Guerry and Wallmeier (2017) surveyed the non-interest rates of banks in 35 countries or regions and the results are shown in Table 1.

variable. Panel A and panel B show the results of income and asset diversification, respectively.

In panel A, the results reveal a nonlinear relationship between ROA and income diversification. The coefficients of **noninterestratio** are positively significant at the 5% level in column (1), which suggests that banks engaging more in non-interest business tend to achieve higher ROA. The quadric term of non-interest ratio, **noninterestratiosq**, in columns (2) is negatively significant, implying an inverted U-shaped relationship between ROA and non-interest ratio. To further justify the nonlinear relationship, I perform the "utest" proposed by Lind and Mehlum (2010), which examines whether the sign of slope is significant in either the left- or right-hand interval. The result shows that the possibility (P-value) of rejecting the inverted U-shaped relationship is 0.022, and the turning point (-coef_noninterestratio/ 2*coef_noninterestratiosq) for this inverted U-shaped relationship is 0.340, which approximately corresponds to the 85th percentile. This implies that when the non-interest income ratio is below the turning point, engaging more in non-interest businesses is beneficial for bank profitability. On the contrary, the positive effect will disappear or even turn negative if the ratio exceeds the turning point.

Similar results are observed when **incomeHHI** is served as the independent variable. The coefficient of **incomeHHI** is positive and significant at the 1% level in columns (3), and the quadratic term is negatively significant in columns (4). However, the P-value for rejecting an inverted U-shaped relation is 0.173, implying that the negative effect on ROA is insignificant when banks become more diversified.

On the other hand, we find strong evidence that increased diversification worsens net margin income on interest activities, as the coefficients of diversification variables in columns (5) and (7) are significantly negative. The quadratic terms are insignificant in columns (6) and (8), which suggests no nonlinear relations. The results predict that a one-unit increase in non-interest income share or **incomeHHI** will lead to a decrease in the NIM of 0.008 or 0.006. The negative relationship implies that there may be a cross-subsidization effect, i.e., diversified banks may use loans as a loss leader product as they can be compensated from other products.

Focusing on asset diversification in panel B, I use the one-year lagged asset diversification

to measure a lagged effect on profitability as discussed above. The coefficients of **nonloanasset** are all positively significant, and its quadratic term is significant at the 10% level. However, the "utest" result does not support an inverted U-shaped relationship, and most observations are in the negative-slope interval. This is also confirmed by columns (3) and (4), where only the linear coefficient is negatively significant. These results show that a higher allocation of non-loan assets can improve bank profitability. Similarly, I find that NIM is negatively related to asset diversification in columns (5) and (7), suggesting the loss-leader role of loans.

Overall, the above results suggest that diversification can enhance bank profitability at the expense of declining interest margins, indicating that banks employ interest businesses as loss leaders to promote non-interest products. Nonetheless, it is necessary to reevaluate this strategy in light of the non-linear relationship between return on investment and diversification. More specifically, most traditional Japanese banks focus on loan-making and thus have a relatively lower share in non-interest income or non-loan assets. When they engage more in non-interest businesses, they can endure a decline in interest margins since the diversification effects are still positive. However, as bank diversification increases, the benefits to ROA diminish or even become discounted. In other words, bank diversification yields significant benefits when kept at a relatively low level. This nonlinear relationship may be due to the balancing act between two opposing effects of diversification, as Stiroh and Rumble (2006) suggested. When diversification remains relatively lower, the marginal benefits from non-interest businesses outweigh the costs. However, as diversification increases, the costs gradually dominate, potentially explaining why many studies have observed diversification discounts in the U.S. and European markets.

I also find that capital ratio, OHR, fund cost, and non-performing loan ratio significantly affect bank profitability. Banks with a high capital ratio are found to have a higher ROA. The reason may be that low-leverage banks are more efficient in management, which helps banks obtain high profitability. The negative coefficients of OHR and fund cost show that cost-efficient banks are more profitable. As for the non-performing loan, it is easy to understand that banks with a lower non-performing loan ratio perform better since it can be regarded as a

possible loss for banks.

2.5.2 Risk and bank diversification

I then examine whether bank diversification will affect bank risk. The standard deviation of ROA and Z-score are used as the dependent variable. Table 2-6 shows the results for the impact of diversification on the earnings stability and bankruptcy risk.

Across all regression specifications, I find that only asset diversification shows a risk-reducing effect. The coefficients for income diversification variables are not statistically significant in Panel A, Table 2-6, suggesting that income diversification may not have a significant impact on bank risk. On the contrary, it suggests that a diversified portfolio of bank assets can mitigate bank risk. In Panel B, Table 2-6, the coefficients of the non-loan asset ratio and its quadratic term are statistically significant in column (2), revealing a U-shaped relationship between asset diversification and earnings stability. This finding indicates that when the non-loan asset ratio falls below 0.407, equivalent to the 79th percentile, an increase in the non-loan asset ratio contributes to enhanced earnings stability. However, it turns into an increase in bank risk if the ratio exceeds 0.407, as justified by the U-test with a p-value of 0.011. Furthermore, the negative sign of **assetdiversity** in column (3) confirms a similar risk-reducing effect, indicating a high reliance on loan businesses or other non-loan businesses brings more fluctuation in earnings. Meanwhile, there is no evidence of a nonlinear relationship for asset diversity as its quadratic term is insignificant in column (4). This is reasonable because an increase in the non-loan asset ratio will decrease the value of **assetdiversity** if the non-loan asset ratio exceeds 0.5. On the other hand, I also find that asset diversification is positively linked with Z-score. The coefficient of **assetdiversify** is positively significant at the 1% significant level in column (7), implying that banks with higher asset diversification have a lower bankruptcy risk. Although the sign of the non-loan assets ratio is positive but insignificant in column (5), it becomes marginally significant after introducing its quadratic term.

To sum up, engaging more in non-loan businesses can decrease bank risk for most banks that

rely on traditional lending businesses. In contrast, banks with a large proportion of non-loan assets are found to be more risky. These results support the portfolio theory that diversified asset allocation can reduce risk. This result is partly consistent with Sawada (2013)'s suggestion of a negative relationship between market-measured risk and non-interest income ratio in the Japanese banking industry. He finds that banks with a higher non-interest ratio have a lower total risk measured by the standard deviation of stock returns.

Regarding the control variables, Table 2-6 reveals that the capital ratio is inversely correlated with bank risk, while NPL has a positive association with risk. As previously discussed, a higher capital ratio not only enhances bank profitability but also mitigates bank risk. This effect may be attributed to a greater loss-absorbing capacity and more prudent management associated with higher capital ratios. Conversely, an increase in non-performing loans (NPL) does indeed raise bank risk, aligning with our expectations.

2.5.3 Endogeneity

The above results show that bank diversification significantly correlates with performance, but the regression results may be inconsistent due to endogeneity problems. Even though employing the fixed effects model can partly alleviate endogeneity, it may also suffer from other endogeneity problems, such as reverse causality. In the case of bank diversification, banks with higher profitability or lower risk may be more willing to increase diversification because they have the spare capacity to develop new businesses or take risks. Therefore, I use the instrumental variable regressions to control for the endogeneity.

In prior studies, some researchers used the lag of endogenous variable as the instrumental variable, such as Elsas et al. (2010) and Demirgüç-Kunt and Huizinga (2010). However, the lagged terms only postpone the original channel of endogeneity, and estimations are still biased if the assumption of no dynamics among unobservables is not satisfied (Bellemare et al., 2017). Following Laeven and Levine (2009), I use the average diversification of other banks that belong to the same type and region[9] as an extra instrumental variable. The advantage of this

[9] There are seven regions in Japan:Tōhoku (Hokkaidō is included in Tōhoku due to a limited bank sample), Kantō, Chūbu, Kinki, Chūgoku and Shikoku, Kyūshū.

instrumental variable is that banks may imitate the behavior of similar banks, but the diversification level of other banks will not affect the given bank's performance.

Table 2-7 shows the results for the two-stage least squares regressions(2sls) on profitability. In the first-stage regression, the instrument is statistically significant at the 1% significant level in most regression, suggesting they are not weak instruments. I also find that the Kleibergen-Paap rk Wald F value and Hansen J value confirm the validity of IVs. As can be seen from columns (1)-(4), Panel B, the coefficients for instrumented income diversification variables are not statistically significant, whereas the coefficients for the instrumented asset diversification variable exhibit the same sign as those in the baseline regression and attain statistical significance. It supports that banks with a higher asset diversification have a better performance in profitability after considering endogeneity. While I do not find significant results on income diversification for the entire data period, the estimation results become significant after 2008. The results are shown in Appendix, Table A2-1, which indicates that the diversification benefits on profitability are at least robust after 2008. As for NIM in columns (5)-(8), the findings imply that more diversified banks, no matter in income or assets, tend to exhibit lower interest margins, which is consistent with the results from baseline regressions.

While the two IVs exhibit favorable properties in the regression analysis for profitability, they do not pass the overidentification test when bank risk is regressed. To get more IVs, I follow the method proposed by Lewbel (2012) to generate heteroskedasticity-based instruments from the error structure of the first-stage IV regression. Table 2-8 shows the results from the Lewbel model with the external and generated instruments. The results for instrumented income diversification variables are not reported since the coefficients remain insignificant. I find that the heteroskedasticity-based instruments are satisfactory, as the condition of "Kleibergen-Paap rk Wald F > Stock-Yogo weak ID test critical values at 5%" is met, and there is no evidence against the hypothesis of exogenous instruments according to the Hansen J value. From the regression results, the negative relationship between asset diversification and bank risk still holds, corroborating previous results that diversification can reduce bank risk.

2.5.4 Additional robustness tests

2.5.4.1 Alternative measures of income diversification

In the baseline specification, the non-interest income ratio is used to measure bank income diversification. However, not all non-interest activities can be considered part of non-traditional bank activities. Rogers (1998) suggests that service charges earned on deposits are also a traditional bank activity. Chiorazzo et al. (2018) define traditional activities as interest-generating activities and noninterest financial services to relationship banking customers. These traditional fee-based activities, such as exchange services and fiduciary services, may change in form due to the development of technology, but their basic functions remain unchanged. Therefore, I use a new variable to measure diversification from a traditional banking business perspective.

For a traditional bank, the basic business is the interest and exchange business. Income from the above business can be considered traditional income. Thus, the non-traditional income ratio is defined as:

$$\text{nontraditionratio} = \frac{\text{total income} - \text{interest} - \text{fees from exchanges}}{\text{interest} + \text{fee and commissions} + \text{trading} + \text{other income}} \quad (5)$$

where fee from exchanges is the income from exchange services and is listed as an individual item in banks' income statement. In addition to that, I also employ the same method of calculating **assetdiversity** to measure the new income diversification (traditiondiversity), which is equal to 1-|2*nontraditionratio-1|.

Table 2-9 shows the impact of alternative income diversification variables on bank profitability[10]. The results are quite similar to the previous results in Table 2-5. The findings that there are nonlinear relationships between income diversification and bank profitability still hold. What is more, this also suggests that while noninterestratio might overestimate bank diversification by ignoring the deposit-related fee business, it is still an appropriate proxy for bank diversification.

[10] The results for risk are still insignificant and therefore not shown.

2.5.4.2 Subsamples and the effect of the financial crisis

The sample period in the baseline analysis is 2000 to 2022, which may be so long as to ignore changes in the bank diversification effect. In particular, some researchers, such as Guerry and Wallmeier (2017), argue that the diversification effect disappeared to zero after the 2008 financial crisis. In this context, it is necessary to re-examine the diversification effect considering the time factor.

It is a natural choice to use the 2008 financial crisis as a dividing time point. The sample period is divided into pre-crisis (2000-2006) and post-crisis (2010-2020). I repeat the baseline model in the two subsamples, and the results are shown in Table 2-10. Panel A presents the results on profitability[11]. Columns (1)-(2) and (5)-(6) show that bank diversification variables are still positively linked with ROA in two subsamples, implying that even after the crisis, banks can improve their profitability by diversifying their operations. Similarly, the relationship between bank diversification and NIM remains significantly negative in pre- and post-crisis periods. As for bank risk in Panel B, the results show a different pattern in two periods, where the risk-decline effects become insignificant before the crisis. As in the baseline regression, the impact of the income diversification variable on bank risk is insignificant (results not shown). In contrast, the nonlinear relationship between the non-loan assets ratio and risk remains significant after the crisis. One reason for the insignificant results in the pre-crisis period may be that the observations are limited compared to the post-crisis period. To address this issue, I introduce the interaction terms of diversification with two dummy variables that categorize the entire period into pre-crisis, mid-crisis, and post-crisis, to measure possible changes after the 2008 financial crisis. The results are shown in Appendix, Table A2-2, where the coefficients of the interaction terms are insignificant except for the impact on the NIM after the crisis. This suggests that banks have become less incentivized to sacrifice profits from the loan business to promote new businesses after the crisis. Overall, the above analysis indicates that the relationship between bank diversification and performance remains robust after the

[11] The results on incomeHHI and assetdiversity are similar to the variables shown in Table 2-9 but not reported due to space limitations.

crisis.

2.6. Further analysis

2.6.1 The effects of bank types

The above results suggest opposite diversification effects for banks with different levels of diversification. It raises a concern of whether it can be attributed to the type of bank since different types of banks are not equally distributed in terms of bank diversification, as shown in Figure 2-2. Most regional banks and second regional banks evolved from traditional Japanese banks, which concentrate on loan-making and thus have a relatively lower diversification. In contrast, city banks are significantly more diversified and complex than other banks. Despite the fact that the diversification level of regional and second regional banks has continued to increase and doubled over the past two decades, the mean values of diversification variables nowadays are currently smaller than those of city banks in 2000. Even though there are some fluctuations in the trends, city banks have become slightly more diversified than in the past, especially in asset allocation. An evident upward trend in the non-loan asset ratio(nonloanasset) suggests that traditional loans are expanding at a slower pace compared to other assets.

On the other hand, online banks[12] have a different business model. Unlike traditional banks, they were initially highly dependent on fee-generating businesses or non-loan assets, resulting in extremely high values in non-interest income ratio(noninterestratio) and non-loan assets ratio(nonloanasset) and lower values in the other two diversification variables(incomeHHI, assetdiversity). However, though they still exhibit a high reliance on non-traditional banking businesses, the diversification variables indicate a trend toward alignment with the regional banks. This suggests that online banks are trying to expand their loan businesses, which is also a diversification strategy for online banks, but in the opposite direction. Due to the

[12] In this section, I focus on online banks rather than new forms banks because most new forms banks are online banks except for Shinsei bank, Aozora bank, and Japan post bank. The latter is more like traditional banks but can operate nationwide, which is different from regional banks.

heterogeneity among different types of banks, I discuss the diversification effect across banks to analyze the nonlinear relationship further.

Firstly, three interaction terms between type dummies and diversification are introduced to test whether bank type will affect the relationship between bank diversification and performance. The variables **Second**, **City,** and **Online,** denote dummy variables for second regional banks, city banks, and online banks, respectively. Table 2-11 presents the results of the moderating effects on bank profitability and risk. Panel A shows a significant difference in profitability among different banks. The coefficients for **Second** are positively significant in columns (1) and (2), while the coefficients for **City** and **Online** are negative when multiplied with income diversification measures. I also test whether the three dummy variables are jointly significant and then calculate the marginal effects on bank profitability for different banks based on the base effect and the interaction terms. These results confirm that diversification in revenue improves bank profitability for regional banks and second regional banks, and the margin effect for second regional banks is slightly larger than for regional banks. In contrast, the effect is statistically insignificant for city banks and even turns out to be negatively significant for online banks, suggesting no diversification benefits but discounts. This is consistent with the non-linear relationship between diversification and profitability found in panel A, Table 2-5. For city banks, it may be costly but cannot yield the expected high returns if they are eager to expand and earn more from new businesses since they are already complex in their operations under the existing regulations. However, online banks can improve their profitability by expanding their lending business, as confirmed by the results of asset diversification variables in columns (3) and (4). The marginal effects of asset diversification also show that the positive effects are more pronounced for second regional banks and city banks compared with regional banks.

Regarding Net Interest Margin (NIM), the findings in columns (5) - (8) imply that all banks are employing loans as a loss leader to promote non-interest businesses. Notably, city banks and online banks appear more inclined to adopt this strategy, as the negative marginal effects are more pronounced. This result may be related to the fact that city banks have the lowest

funding costs, while online banks are actively seeking to expand their market share.

Panel B presents the results of the moderating effect on risk. The results in columns (3), (4), (7), and (8) indicate that asset diversification has a risk-reducing effect on regional banks, city banks, and online banks. The results suggest that city banks and regional banks can reduce risk by allocating fewer assets to lending businesses, while online banks should increase the share of loans.

The above results indicate that the relationship between bank diversification and performance may vary across groups, resulting in nonlinear relations found in the baseline regressions. To further eliminate the effect of bank type, I re-test the nonlinear relationship in the subsample of regional banks or second regional banks, and the results are presented in Appendix, Table A2-3. The results of the subsample regressions show that the nonlinear relationship between ROA and income diversification remains unchanged, while other nonlinear relationships become insignificant. This confirms that sample selection may be responsible for some of the potential nonlinear relationships.

2.6.2 The decomposition of non-interest income

Banks can diversify their revenue by expanding into different business areas, which raises the concern about which businesses contribute to the positive diversification effect. Generally, the non-interest income can be divided into fees and commissions, trading, and other income. Table 2-12 shows the regression results of performance regressed on the revenue share of three different businesses. The results suggest that the ratio of fees and commissions to total ordinary income (**fee income**) has a negative effect on banks' ROA, while **trading income** and **other income** can improve bank profitability. This may be counterintuitive as fees and commissions are usually considered a stable source of income with lower costs. The negative impact on ROA could be attributed to the observed decline in net interest margins, as illustrated in column (5), Panel A. Moreover, the coefficient of **fee income** is larger than that of trading and other income, indicating that banks are sacrificing a larger portion of their net interest margin income to promote fees and commissions businesses than other types of businesses. I also find that the total profit from interests and fees and commissions businesses is negatively correlated with

fee income, implying that gains from fees and commissions businesses cannot compensate the costs due to the loss leader effect. A possible negative relationship between fee income and profitability has also been confirmed for the South Asian countries (Nisar et al., 2018) and U.S. (DeYoung and Rice, 2004b). To be more cautious, it is worth noting that some studies provide the opposite evidence. For example, Sawada (2013) finds that fee income has a positive effect on Japanese banks' market performance measured by Tobin's Q and the ME/BE ratio.

As for bank risk in Panel B, only **fee income** is negatively correlated with **logzcsore** at the 10% significant level in column (5). This result indicates that banks with a higher share of fee and commission income are more stable, which is consistent with the finding of Sawada (2013). Expanding in trading may increase bank risk, but the coefficients are not significant. This may explain why the non-interest income ratio is not significant in the baseline regression.

2.6.3 Bank diversification effects during the crisis

Diversification strategies have been found to increase profits and reduce risk through a 23-year sample. I wanted to test whether the diversification strategy is a solution to an unexpected crisis or, in other words, whether more diversified banks perform better during a crisis. Thus, following Stiroh and Rumble (2006), I conduct similar cross-sectional regressions during the 2008 financial crisis (2007-2009) and the COVID-19 pandemic (2020-2022). The specification is set as:

$$\overline{Performance_i} = \alpha + \beta Diversification_i + \gamma \overline{Controls_i} + \varepsilon_i \qquad (6)$$

, where the dependent variable is the mean value of ROA, the standard deviation of ROA, and the logarithm of Z-score[13] during the crisis period. Bank diversification is assumed to be relatively stable and measured by the average of the diversification levels in the two years prior to the crisis. This is reasonable as banks may not be able to restructure their business quickly and, more importantly, we want to assess the impact of maintaining a high level of

[13] The value of Z-score is calculated by $\frac{\overline{ROA}+\overline{E/A}}{\sigma_{ROA}}$

diversification. Other control variables are also calculated as their average values during the crisis period.

Table 2-13 suggests a different story regarding the diversification effects during the crisis period. The results on income diversification show that banks with a higher non-interest ratio tend to exhibit lower profitability and higher risk during the crisis period. Conversely, banks that are more diversified in assets are lower in NIM but less risky. The opposite results on risk may be explained by the difference in measurement methods as the correlation indices between the two measures are 0.38(the 2008 financial crisis) and 0.33(the COVID-19 pandemic), which are smaller than that for the entire sample. It suggests that two variables measure different aspects of bank activities. The non-interest operations are more sensitive to market fluctuations and economic downturns, and a portion of these businesses are not accounted for in asset diversification. The decomposition effects of the non-interest ratio reveal that trading and other income businesses positively relate to bank risk during the crisis[14]. In order to relax the assumptions about diversification, the average level of diversification during the crisis is used as a new independent variable. The results are reported in Appendix, Table A2-4, and the sign of key variables remains unchanged.

The above results based on different diversification measures raise the concern of which standards are preferred. As noted by Guerry and Wallmeier (2017), there is no preference in the choice of measurements, which remains an open question. However, researchers should be cautious and pay attention to the possible differences caused by variable selection in future studies.

2.7. Conclusion

This paper provides a comprehensive analysis of the relationship between bank diversification and profitability and risk performance in the Japanese banking industry. In order to accurately reflect the extent to which banks engage in non-traditional business, diversification is measured

[14] Risk measures are regressed on the average values of trading income ratio and other income ratio in the two years prior to the crisis (detailed results are not presented due to the space limitation).

from income and asset perspectives. The sample encompasses a wide range of banks, including traditional lending-focused commercial banks and emerging online banks, offering a holistic understanding of the Japanese banking landscape.

The findings of this study reveal a positive relationship between bank diversification and Return on Assets (ROA). Strong evidence shows that most Japanese banks can improve their profitability from non-interest businesses. However, the marginal effects are found to decrease as banks become more diversified, suggesting the presence of a nonlinear relationship, especially for income diversification. In other words, diversification effects on profitability are positively significant when banks are less diversified, while highly diversified banks do not experience the same benefit. This nonlinearity is further confirmed when assessing the diversification effects across different types of banks in Japan. Compared to other banks, second regional banks that highly depend on lending business exhibit a larger marginal effect. In contrast, city banks and online banks experience diversification discounts. One plausible reason for such a nonlinear relationship is that as banks become more diversified, the diversification benefits, such as economies of scope and synergy effects, are gradually offset by negative effects. Another cost of diversification is the decline in net interest margins. There is a negative relationship between net interest margins and diversification, indicating that banks are using the interest business as a loss leader to promote other businesses. This is particularly evident in the case of city banks and online banks, which demonstrate a higher willingness to trade interest income to advance non-interest revenue streams.

Concerning bank risk, a risk-declining effect is only observed for asset diversification. Banks that are more diversified in assets have lower earnings volatility and bankruptcy risk, while it is insignificant for income diversification. A decomposition analysis of non-interest businesses reveals varied effects on bank risk. The results suggest that fee income can reduce bank risk, while trading businesses are more risky. This may explain why income diversification is not significantly correlated with bank risk. On the other hand, under crisis periods such as the 2008 financial crisis and the COVID-19 pandemic, an opposing effect emerges for income and asset diversification. Banks diversified in assets tend to exhibit lower risk during crisis periods, while

banks diversified in income are found to be more risky.

For bank decision-makers, this study suggests that the diversification strategy may be a solution to improve bank performance only if the bank is less diversified. They should pay attention to the cost of diversification in using loans as a loss leader and the risk of different bank businesses. For the regulators, it also provides some evidence about the heterogeneity in diversification effects among banks with different diversification levels or types, which can be helpful in developing flexible regulation. Lastly, it is important to note that this paper only reports the net effect of bank diversification. In other words, the specific mechanisms through which diversification affects bank performance are still not clear. Though some studies have referred to possible channels of diversification effects, finding appropriate proxies for the media effect is still challenging. Therefore, more empirical studies are needed to explore the mechanism further.

Tables

Table 2-1 Sample distribution

Year	City bank	Regional bank	Second regional bank	New forms bank		Total
				online bank	others	
2000	3	61	45	0	0	109
2001	3	61	46	0	0	110
2002	4	61	46	0	0	111
2003	5	63	47	0	0	115
2004	5	64	48	2	1	120
2005	5	64	47	2	1	119
2006	5	64	46	3	2	120
2007	5	64	45	3	2	119
2008	5	64	44	3	2	118
2009	5	65	42	4	2	118
2010	5	64	42	5	3	119
2011	5	65	42	6	3	121
2012	5	65	41	6	3	120
2013	4	65	41	6	3	119
2014	4	65	41	7	3	120
2015	4	65	41	8	3	121
2016	4	65	41	8	3	121
2017	4	65	41	8	3	121
2018	4	65	40	8	3	120
2019	4	64	37	8	3	116
2020	4	60	37	8	3	112
2021	4	59	36	8	3	110
2022	4	59	36	8	3	110
Total	100	1457	972	111	49	2689

Note: this table presents the distribution of different types of Japanese commercial banks in the sample. Generally, commercial banks in Japan are categorized into city banks, regional banks, second regional banks and new forms banks. In this study, new forms banks are further subdivided into online banks and others. The former typically operate without physical branches, offering services through online platforms or ATMs. Online banks include Sony Bank (2004), Seven Bank (2004), Rakuten Bank(2006), Aeon Bank (2009), SBI Sumishin Net Bank (2010), AU Jibun Bank (2011), Daiwa Next Bank (2014). Paypay Bank (2015). Others include SBI Shinsei Bank (2004), Aozora Bank (2006), and Japan Post Bank (2010). The year in parentheses indicates when each bank was initially included in the study.

Table 2-2 Variable description

Variable	Description
Dependent variables	
ROA	Return on average assets $$\text{ROA} = \frac{\text{net income}_t}{(\text{total assets}_{t-1} + \text{totoal assets}_t) \,/\, 2}$$
NIM	Net interest margin, (interest income – interest expense) / earning assets
sdROA	The standard deviation of ROA based on the past three years (t,t-1,t-2)
logzscore	The natural logarithm of the Z-score $\text{zscore} = \frac{\text{ROA+CAR}}{\sigma_{\text{ROA}}}$
Independent variables	
noninterestratio	The ratio of non-interest income to total ordinary income $$\text{noninterestratio} = \frac{\text{fee and commissions} + \text{trading} + \text{other income}}{\text{interest} + \text{fee and commissions} + \text{trading} + \text{other income}}$$ fee and commissions are equal to the original item plus trust fees.
incomeHHI	$$\text{incomeHHI} = 1 - \left(\frac{\text{interet}}{\text{total income}}\right)^2 - \left(\frac{\text{fee and commissions}}{\text{total income}}\right)^2 - \left(\frac{\text{trading}}{\text{total income}}\right)^2 - \left(\frac{\text{other income}}{\text{total income}}\right)^2$$
nonloanasset	1 - the ratio of loan to total earning assets
assetdiversity	$$\text{assetdiversity} = 1 - \frac{\lvert\text{loans} - \text{other earning asset}\rvert}{\text{total earning asset}}$$
Control variables	
logasset	Bank size, the natural logarithm of total assets
capitalratio	Equity / total assets
OHR	Overhead costs / gross operating profits
fundcost	Interest expenses$_t$ / ((deposit$_{t-1}$ +deposit$_t$)/2)
assetgrowth	Asset growth rate, (total assets$_t$ - total assets$_{t-1}$)/assets$_{t-1}$
NPL	The ratio of non-performing loan
BHC	Dummy variable, if the bank is affiliated with a BHC, it is equal to 1

Table 2-3 Descriptive statistics

	N	Mean	Std. Dev.	Min	Median	Max
Dependent variables						
ROA	2689	0.001	0.004	-0.018	0.002	0.011
NIM	2689	0.014	0.005	0.004	0.014	0.025
sdROA	2407	0.002	0.003	0	0.001	0.018
logzscore	2407	4.244	1.423	0.319	4.516	7.065
Independent variables						
noninterestratio	2689	0.255	0.091	0.101	0.241	0.633
incomeHHI	2689	0.395	0.100	0.151	0.392	0.621
nonloanasset	2689	0.345	0.125	0.144	0.324	0.962
assetdiversity	2689	0.640	0.174	0.075	0.637	0.989
Control variables						
logasset	2689	14.756	1.204	12.472	14.719	19.087
capitalratio	2689	0.049	0.015	0.019	0.048	0.106
OHR	2689	0.716	0.115	0.437	0.718	1.107
fundcost	2689	0.002	0.002	0	0.001	0.012
assetgrowth	2689	0.028	0.052	-0.085	0.019	0.251
NPL	2689	0.037	0.026	0	0.030	0.127
BHC	2689	0.202	0.401	0	0	1

Table 2-4 Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) noninterestratio	1.000										
(2) incomeHHI	0.815***	1.000									
(3) nonloanasset	0.541***	0.277***	1.000								
(4) assetdiversity	0.193***	0.404***	0.311***	1.000							
(5) logasset	0.396***	0.492***	0.391***	0.428***	1.000						
(6) capitalratio	0.130***	-0.057***	0.188***	0.035*	0.055***	1.000					
(7) OHR	-0.050***	-0.018	-0.074***	-0.076***	-0.437***	-0.164***	1.000				
(8) fundcost	0.068***	-0.010	0.181***	-0.011	0.213***	0.026	-0.242***	1.000			
(9) assetgrowth	0.227***	0.173***	0.288***	0.153***	0.126***	0.034*	-0.082***	-0.035*	1.000		
(10) NPL	-0.474***	-0.430***	-0.390***	-0.201***	-0.360***	-0.208***	-0.060***	0.064***	-0.327***	1.000	
(11) BHC	0.277***	0.325***	0.046**	0.103***	0.348***	-0.162***	-0.125***	0.036*	0.082***	-0.239***	1.000

Note: This table presents Pearson correlation coefficients between independent variables and control variables. The superscripts *, **, *** denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table 2-5 Regression results for bank diversification and profitability

Panel A: income-based diversification	(1) ROA	(2) ROA	(3) ROA	(4) ROA	(5) NIM	(6) NIM	(7) NIM	(8) NIM
noninterestratio	0.005**	0.034***			-0.008***	0.006		
	(0.002)	(0.010)			(0.002)	(0.011)		
noninterestratiosq		-0.050**				-0.021		
		(0.019)				(0.022)		
incomeHHI			0.006***	0.023***			-0.006***	0.001
			(0.001)	(0.007)			(0.001)	(0.006)
incomeHHIsq				-0.022**				-0.009
				(0.009)				(0.008)
logasset	-0.000	-0.001	-0.000	-0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
capitalratio	0.142***	0.141***	0.142***	0.142***	0.043**	0.043**	0.044**	0.044**
	(0.021)	(0.021)	(0.021)	(0.021)	(0.018)	(0.018)	(0.017)	(0.017)
OHR	-0.010***	-0.010***	-0.010***	-0.010***	-0.005***	-0.005***	-0.005***	-0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
fundcost	-0.166**	-0.213***	-0.178**	-0.200**	-0.466***	-0.486***	-0.465***	-0.474***
	(0.077)	(0.075)	(0.079)	(0.077)	(0.110)	(0.111)	(0.119)	(0.119)
assetgrowth	0.009***	0.009***	0.009***	0.009***	-0.004**	-0.004***	-0.004**	-0.004**
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
NPL	-0.061***	-0.062***	-0.061***	-0.061***	0.026***	0.025***	0.026***	0.026***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.004)	(0.004)	(0.004)	(0.004)
BHC	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
_cons	0.011	0.010	0.010	0.006	0.019	0.018	0.018	0.017
	(0.015)	(0.015)	(0.016)	(0.017)	(0.022)	(0.022)	(0.021)	(0.021)
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	2689	2689	2689	2689	2689	2689	2689	2689
R^2(within)	0.389	0.401	0.392	0.396	0.843	0.845	0.839	0.839

(Continued on next page)

Table 2-5 (Continued)

Panel B: asset-based diversification	(1) ROA	(2) ROA	(3) ROA	(4) ROA	(5) NIM	(6) NIM	(7) NIM	(8) NIM
l.nonloanasset	0.005**	0.023**			-0.009***	-0.005		
	(0.002)	(0.009)			(0.003)	(0.010)		
l.nonloanassetsq		-0.021*				-0.005		
		(0.012)				(0.014)		
l.assetdiversity			0.004***	0.009			-0.003**	0.004
			(0.001)	(0.008)			(0.001)	(0.008)
l.assetdiversitysq				-0.003				-0.005
				(0.006)				(0.005)
logasset	-0.001	-0.002***	-0.002**	-0.001	-0.001	-0.002	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
capitalratio	0.139***	0.135***	0.134***	0.139***	0.035**	0.034**	0.044**	0.043**
	(0.022)	(0.020)	(0.022)	(0.022)	(0.016)	(0.014)	(0.019)	(0.018)
OHR	-0.010***	-0.011***	-0.011***	-0.010***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
fundcost	-0.184**	-0.143*	-0.141*	-0.184**	-0.492***	-0.482***	-0.570***	-0.554***
	(0.083)	(0.074)	(0.082)	(0.083)	(0.131)	(0.129)	(0.144)	(0.135)
assetgrowth	0.009***	0.009***	0.010***	0.009***	-0.006***	-0.006***	-0.006***	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
NPL	-0.056***	-0.055***	-0.055***	-0.056***	0.021***	0.022***	0.023***	0.023***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.004)	(0.004)	(0.005)	(0.004)
BHC	0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
cons	0.020	0.031**	0.035**	0.020	0.041**	0.044**	0.025	0.025
	(0.017)	(0.014)	(0.018)	(0.017)	(0.016)	(0.018)	(0.019)	(0.020)
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year-fixed	YES	YES	YES	YES	YES	YES	YES	YES
N	2548	2548	2548	2548	2548	2548	2548	2548
R^2(within)	0.396	0.403	0.401	0.402	0.870	0.870	0.861	0.862

Note: This table examines the relationship between bank diversification and profitability. Panel A reports the results of income diversification, and Panel B presents the results of asset diversification. The quadratic terms of independent variables are also introduced in the model to test a nonlinear relationship. For example, noninterestratiosq is the quadratic term of noninterestratio, and so are other independent variables. Specifications include individual, year-fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts *, **, *** denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table 2-6 Regression results for bank diversification and risk

Panel A: income-based diversification	(1) sdROA	(2) sdROA	(3) sdROA	(4) sdROA	(5) logzscore	(6) logzscore	(7) logzscore	(8) logzscore
noninterestratio	0.000	-0.001			-0.133	-0.271		
	(0.002)	(0.009)			(0.510)	(1.760)		
noninterestratiosq		0.002				0.236		
		(0.016)				(2.708)		
incomeHHI			0.000	0.000			-0.169	-0.374
			(0.001)	(0.007)			(0.440)	(1.937)
incomeHHIsq				0.000				0.249
				(0.008)				(2.278)
logasset	-0.002	-0.002	-0.002	-0.002	0.702**	0.702**	0.700**	0.698**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.293)	(0.293)	(0.293)	(0.294)
capitalratio	-0.074***	-0.074***	-0.074***	-0.074***	46.090***	46.095***	46.059***	46.065***
	(0.021)	(0.021)	(0.021)	(0.021)	(7.001)	(6.985)	(7.000)	(6.988)
OHR	0.002	0.002	0.002	0.002	-1.447***	-1.448***	-1.447***	-1.449***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.424)	(0.426)	(0.424)	(0.429)
fundcost	0.278**	0.280**	0.277**	0.277**	-54.731	-54.517	-54.357	-54.142
	(0.122)	(0.123)	(0.121)	(0.122)	(34.501)	(34.669)	(34.424)	(34.703)
assetgrowth	-0.006***	-0.006***	-0.006***	-0.006***	0.710	0.714	0.712	0.714
	(0.002)	(0.002)	(0.002)	(0.002)	(0.613)	(0.615)	(0.610)	(0.610)
NPL	0.057***	0.057***	0.057***	0.057***	-19.223***	-19.216***	-19.203***	-19.196***
	(0.011)	(0.011)	(0.011)	(0.011)	(2.575)	(2.566)	(2.572)	(2.569)
BHC	0.000	0.000	0.000	0.000	-0.065	-0.065	-0.065	-0.065
	(0.000)	(0.000)	(0.000)	(0.000)	(0.118)	(0.118)	(0.118)	(0.118)
_cons	0.024	0.024	0.024	0.024	-6.605	-6.583	-6.541	-6.480
	(0.019)	(0.020)	(0.019)	(0.021)	(4.586)	(4.608)	(4.602)	(4.665)
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	2407	2407	2407	2407	2407	2407	2407	2407
R^2(within)	0.327	0.327	0.327	0.327	0.459	0.459	0.459	0.459

(Continued on next page)

Table 2-6 (Continued)

Panel B: asset-based diversification

	(1) sdROA	(2) sdROA	(3) sdROA	(4) sdROA	(5) logzscore	(6) logzscore	(7) logzscore	(8) logzscore
l.nonloanasset	0.000	-0.015**			0.468	4.280*		
	(0.002)	(0.006)			(0.865)	(2.470)		
l.nonloanassetsq		0.019**				-4.620		
		(0.008)				(2.973)		
l.assetdiversity			-0.002**	-0.006			1.073***	-0.931
			(0.001)	(0.006)			(0.407)	(1.710)
l.assetdiversitysq				0.003				1.552
				(0.004)				(1.202)
logasset	-0.002	-0.001	-0.001	-0.001	0.728**	0.530*	0.527*	0.563*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.298)	(0.306)	(0.282)	(0.285)
capitalratio	-0.074***	-0.070***	-0.074***	-0.074***	46.596***	45.751***	46.382***	46.631***
	(0.021)	(0.021)	(0.021)	(0.021)	(7.073)	(7.102)	(6.938)	(6.980)
OHR	0.002	0.002	0.002*	0.002*	-1.480***	-1.523***	-1.564***	-1.561***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.425)	(0.420)	(0.410)	(0.404)
fundcost	0.277**	0.244**	0.284**	0.276**	-59.086*	-51.109	-57.479*	-61.359*
	(0.125)	(0.122)	(0.123)	(0.120)	(35.194)	(35.407)	(34.327)	(33.902)
assetgrowth	-0.006***	-0.006***	-0.007***	-0.007***	0.809	0.787	1.029	1.157*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.635)	(0.631)	(0.624)	(0.633)
NPL	0.057***	0.056***	0.056***	0.056***	-19.064***	-18.805***	-18.520***	-18.504***
	(0.011)	(0.012)	(0.012)	(0.012)	(2.638)	(2.722)	(2.742)	(2.704)
BHC	0.000	0.000	0.000	0.000	-0.059	-0.063	-0.051	-0.049
	(0.000)	(0.000)	(0.000)	(0.000)	(0.117)	(0.116)	(0.119)	(0.120)
_cons	0.024	0.014	0.020	0.020	-7.159	-4.898	-4.674	-4.605
	(0.019)	(0.018)	(0.019)	(0.018)	(4.661)	(4.677)	(4.365)	(4.399)
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year-fixed	YES	YES	YES	YES	YES	YES	YES	YES
N	2407	2407	2407	2407	2407	2407	2407	2407
R^2(within)	0.327	0.334	0.330	0.331	0.459	0.461	0.463	0.464

Note: This table examines the relationship between bank diversification and risk, measured by the standard deviation of ROA and logzscore (the natural logarithm of Z-score), respectively. Panel A reports the results of income diversification, and Panel B presents the results of asset diversification. The quadratic terms of independent variables are also introduced in the model to test a nonlinear relationship. For example, noninterestratiosq is the quadratic term of noninterestratio, and so are other independent variables. Specifications include individual, year-fixed effects, and robust standard errors clustered at the bank level. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table 2-7 Endogeneity: IV regressions

	(1) noninterestratio	(2) incomeHHI	(3) l.nonloanasset	(4) l.assetdiversity
Panel A: First-stage regression				
meandiversification	0.259***	0.122***	0.147***	0.041
	(0.047)	(0.046)	(0.031)	(0.029)
l.diversification	0.460***	0.437***	0.794***	0.731***
	(0.025)	(0.023)	(0.023)	(0.021)
Kleibergen-Paap rk Wald F	206.505	198.836	868.898	629.503
Controls	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Year-fixed	YES	YES	YES	YES
N	2377	2377	2237	2237

Panel B: Second-stage IV(2SLS) regression	(1) ROA	(2) ROA	(3) ROA	(4) ROA	(5) NIM	(6) NIM	(7) NIM	(8) NIM
(instrumented)								
noninterestratio	-0.003				-0.011***			
	(0.003)				(0.002)			
incomeHHI		-0.000				-0.007***		
		(0.002)				(0.001)		
l.nonloanasset			0.005***				-0.008***	
			(0.002)				(0.002)	
l.assetdiversity				0.003**				-0.003***
				(0.001)				(0.001)
Hansen J	2.469	0.107	0.278	0.815	3.701*	1.242	4.081**	0.014
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	2548	2548	2407	2407	2548	2548	2407	2407

Note: This table presents the results controlling for the endogeneity between bank diversification and profitability. The instrumental variables for diversification are the average value of other similar banks' diversification and the one-year lagged diversification variable. In the first-stage regression, the endogenous diversification variable is regressed by the instrument variables and control variables, including logasset, capitalratio, OHR, fundcost, assetgrowth, NPL, BHC**,** and time fixed effects (results are not shown in this table). In the second-stage regression, the fitted value from the first stage and the same controls are used as explanatory variables. Kleibergen-Paap rk Wald F test and Hansen J test confirm the validity of instrumental variables. Specifications include individual, year-fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table 2-8 Endogeneity: Lewbel (2012) method

	(1) sdROA	(2) sdROA	(3) sdROA	(4) sdROA	(5) logzscore	(6) logzscore	(7) logzscore	(8) logzscore
(instrumented)								
l.nonloanasset	-0.000	-0.021***			0.962*	5.864***		
	(0.002)	(0.006)			(0.562)	(1.783)		
l.nonloanassetsq		0.025***				-6.099***		
		(0.007)				(1.950)		
l.assetdiversity			-0.003***	-0.012**			1.670***	-0.919
			(0.001)	(0.005)			(0.325)	(1.353)
l.assetdiversitysq				0.007**				1.894*
				(0.003)				(0.976)
Kleibergen-Paap rk Wald F	91.921	72.508	100.651	24.084	91.921	72.508	100.651	24.084
Hansen J	38.682*	61.177	31.755	52.790	36.854*	67.621	34.610	53.597
External IVs	l2.nonloanasset	l2.nonloanasset (l2.nonloanasset)^2	l2.assetdiversity	l2.assetdiversity (l2.assetdiversity)^2	l2.nonloanasset	l2.nonloanasset (l2.nonloanasset)^2	l2.assetdiversity	l2.assetdiversity (l2.assetdiversity)^2
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	2407	2407	2407	2407	2407	2407	2407	2407

Note: This table presents the results controlling for the endogeneity between bank diversification and risk. Following Lewbel (2012), the instrumental variables are the lagged independent variables and heteroskedasticity-based instruments from the error structure of the first-stage IV regression. The results for income diversification are insignificant and, therefore, are not reported. Control variables include logasset, capitalratio, OHR, fundcost, assetgrowth, NPL, BHC. Cragg-Donald Wald F test and Hansen J test confirm the validity of instrumental variables. Specifications include individual, year-fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table 2-9 Robustness: an alternative measure for income diversification

	(1) ROA	(2) ROA	(3) ROA	(4) ROA	(5) NIM	(6) NIM	(7) NIM	(8) NIM
nontraditionratio	0.005***	0.026***			-0.007***	0.001		
	(0.002)	(0.008)			(0.002)	(0.007)		
nontraditionratiosq		-0.042**				-0.016		
		(0.018)				(0.018)		
traditiondiversity			0.003***	0.012***			-0.003***	-0.001
			(0.001)	(0.004)			(0.001)	(0.003)
traditiondiversitysq				-0.010**				-0.003
				(0.004)				(0.003)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	2689	2689	2689	2689	2689	2689	2689	2689
R^2(within)	0.389	0.397	0.390	0.396	0.839	0.840	0.838	0.838

Note: This table presents the results for the alternative income diversification variables on bank profiability. Nontraditionratio measures the share of income from non-traditional banking bussiness, and traditiondiversity measures the concentration between traditional income and other income. Nontraditionratiosq and traditiondiversitysq are the quadric terms of nontraditionratio and traditiondiversity, respectively. Other control variables (logasset, capitalratio, OHR, fundcost, assetgrowth, NPL, BHC) are included in regressions, but their results are not shown in this table. Specifications include individual, year-fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table 2-10 Robustness: subsamples for pre and post- the 2008 financial crisis

Panel A: Profitability								
	(1) ROA Year<2007	(2) ROA Year<2007	(3) NIM Year<2007	(4) NIM Year<2007	(5) ROA Year>2009	(6) ROA Year>2009	(7) NIM Year>2009	(8) NIM Year>2009
noninterestratio	0.010***		-0.003**		0.004**		-0.007***	
	(0.003)		(0.001)		(0.002)		(0.002)	
l.nonloanasset		0.030***		-0.010***		0.002*		-0.008**
		(0.008)		(0.001)		(0.008)		(0.003)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	804	680	804	680	1530	1403	1530	1403
R^2(within)	0.454	0.476	0.529	0.673	0.430	0.321	0.498	0.450
Panel B: Risk								
	(1) sdROA Year<2007	(2) sdROA Year<2007	(3) logzscore Year<2007	(4) logzscore Year<2007	(5) sdROA Year>2009	(6) sdROA Year>2009	(7) logzscore Year>2009	(8) logzscore Year>2009
l.nonloanasset	-0.010		-0.260		-0.016**		8.889***	
	(0.021)		(8.232)		(0.006)		(2.739)	
l.nonloanassetsq	0.006		5.494		0.020***		-10.271***	
	(0.031)		(11.992)		(0.007)		(2.612)	
l.assetdiversity		-0.004		2.040		-0.002*		1.634***
		(0.004)		(1.240)		(0.001)		(0.579)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	559	559	559	559	1277	1277	1277	1277
R^2(within)	0.225	0.226	0.327	0.328	0.299	0.279	0.146	0.144

Note: This table presents the results of the subsample regression. The sample is divided into pre-2008 financial crisis(2000-2006) and post-2008 financial crisis(2010-2022). Panel A shows the results on profitability, and Panel B presents the results on risk regressed on asset diversification variables only. Columns (1)-(4) are pre-crisis results, and columns (5)-(8) are post-crisis results. Other control variables (logasset, capitalratio, OHR, fundcost, assetgrowth, NPL, BHC) are included in regressions, but their results are not shown in this table. Specifications include individual, year-fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table 2-11Diversification effects and bank type

Panel A: profitability								
	(1) ROA	(2) ROA	(3) ROA	(4) ROA	(5) NIM	(6) NIM	(7) NIM	(8) NIM
noninterestratio	0.006***				-0.003**			
	(0.002)				(0.001)			
incomeHHI		0.005***				-0.003***		
		(0.001)				(0.001)		
l.nonloanasset			0.007***				-0.004**	
			(0.002)				(0.002)	
l.assetdiversity				0.003***				-0.003***
				(0.001)				(0.001)
Second × *Diversification*	0.006**	0.004**	0.004	0.002	-0.003*	-0.002	-0.006**	-0.003*
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)	(0.001)
City × *Diversification*	-0.007*	-0.008	0.012	0.004	-0.009*	-0.013**	0.007**	-0.003
	(0.004)	(0.005)	(0.010)	(0.008)	(0.005)	(0.005)	(0.004)	(0.002)
Online × *Diversification*	-0.030****	-0.024**	-0.013**	0.002	-0.033**	-0.039**	-0.011	0.008
	(0.010)	(0.011)	(0.006)	(0.006)	(0.015)	(0.017)	(0.012)	(0.006)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	2640	2640	2502	2502	2640	2640	2502	2502
R^2(within)	0.397	0.391	0.397	0.394	0.865	0.861	0.883	0.878
F test for type differences of the diversification effect (F-stat)								
F-stat	6.15****	4.22***	2.96**	0.52	3.01**	3.86**	3.61**	2.17*
Marginal effect(coefficient)								
Regional banks	0.006***	0.005***	0.007***	0.003***	-0.003**	-0.003**	-0.004**	-0.003***
Second regional banks	0.012***	0.009***	0.011***	0.005***	-0.006***	-0.005***	-0.010***	-0.005**
City banks	-0.001	-0.003	0.019**	0.007	-0.012**	-0.015***	0.003	-0.005***
Online banks	-0.025**	-0.019*	-0.005	0.005	-0.036**	-0.041**	-0.015	0.005
Panel B: risk								
	(1) sdROA	(2) sdROA	(3) sdROA	(4) sdROA	(5) logzscore	(6) logzscore	(7) logzscore	(8) logzscore
noninterestratio	-0.000				0.292			
	(0.002)				(0.701)			
incomeHHI		0.000				0.252		
		(0.001)				(0.625)		
l.nonloanasset			-0.002				2.043**	
			(0.002)				(0.806)	
l.assetdiversity				-0.001				0.852**
				(0.001)				(0.422)
Second × *Diversification*	-0.001	-0.001	-0.002	-0.001	-1.012	-0.811	0.154	0.113
	(0.003)	(0.002)	(0.004)	(0.002)	(1.097)	(0.875)	(1.719)	(0.856)
City × *Diversification*	0.003	0.005	-0.017**	-0.004	-0.422	-0.427	2.300	1.118
	(0.010)	(0.009)	(0.007)	(0.004)	(1.622)	(1.553)	(1.829)	(1.302)
Online× *Diversification*	0.011	0.012	0.013***	-0.009**	-1.393	-2.076	-6.335***	1.074
	(0.010)	(0.011)	(0.004)	(0.003)	(1.853)	(2.275)	(1.415)	(0.998)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	2364	2364	2364	2364	2364	2364	2364	2364
R^2(within)	0.325	0.325	0.337	0.332	0.454	0.454	0.462	0.457
F test for type differences of the diversification effect (F-stat)								
F-stat	0.59	0.71	8.14***	2.26*	0.37	0.46	8.13***	0.51
Marginal effect(coefficient)								
Regional banks	0	0	-0.002	-0.001	0.292	0.253	2.043**	0.852**
Second regional banks	-0.001	-0.001	-0.003	-0.001	-0.721	-0.558	2.197	0.965
City banks	0.003	0.005	-0.019**	-0.004	-0.131	-0.175	4.343**	1.970
Online banks	0.011	0.013	0.011***	-0.009***	-1.101	-1.824	-4.292***	1.926**

Note: This table presents the moderating effect of bank type on the relationship between diversification and bank performance. Panel A presents the results for profitability, and panel B presents the results for risk. Second, City and Online are three dummy variables, which divide the banks into four categories: city bank, regional bank, second regional bank, and online bank. If a bank belongs to the second regional bank, Second is equal to 1, and if it is a city bank, City is equal to 1. For online banks, Online is equal to 1. The interaction terms of three dummy variables with diversification variables (× Diversification) are included to measure the moderating effect. Other control variables (logasset, capitalratio, OHR, fundcost, assetgrowth, NPL, BHC) are included in regressions, but their results are not shown in this table. Specifications include individual, year-fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively. At the last of panel A, the F test is a joint test for the significance of three dummy variables. Marginal effects for different groups are also calculated based on the coefficients of the interaction terms and the base effect.

Table 2-12 The decomposition of non-interest income

Panel A: profitability								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ROA	ROA	ROA	ROA	NIM	NIM	NIM	NIM
fee income	-0.010*			-0.007	-0.020***			-0.026***
	(0.005)			(0.007)	(0.007)			(0.008)
trading income		0.005***		0.004***		-0.002**		-0.007***
		(0.001)		(0.002)		(0.001)		(0.002)
other income			0.012***	0.013***			-0.009**	-0.012***
			(0.004)	(0.005)			(0.004)	(0.004)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	2689	2689	2689	2689	2689	2689	2689	2689
R^2(within)	0.389	0.388	0.390	0.396	0.846	0.832	0.833	0.857
Panel B: risk								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	sdROA	sdROA	sdROA	sdROA	logzscore	logzscore	logzscore	logzscore
fee income	-0.003			-0.003	2.248*			2.065
	(0.005)			(0.005)	(1.333)			(1.411)
trading income		0.001		0.001		-0.616		-0.259
		(0.001)		(0.001)		(0.495)		(0.511)
other income			-0.001	-0.001			0.227	0.317
			(0.003)	(0.003)			(1.734)	(1.766)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	2407	2407	2407	2407	2407	2407	2407	2407
R^2(within)	0.327	0.327	0.327	0.328	0.461	0.460	0.459	0.461

Note: This table presents the results for the impact of three non-interest businesses on bank performance. Panel A reports the results for profitability, and Panel B presents the results for risk. The income from non-interest businesses can be diveided into: fees and commission, trading, and other income. Fee income is calculated as the proportion of fees and commissions to ordinary income, and similar calculations are applied to the other two measures. Other control variables (logasset, capitalratio, OHR, fundcost, assetgrowth, NPL, BHC) are included in regressions, but their results are not shown in this table. Specifications include individual, year-fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table 2-13 Diversification effects during the crisis

Panel A: the 2008 financial crisis (2007-2009)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ROA_mean	ROA_mean	NIM_mean	NIM_mean	sdROA	sdROA	logzscore	logzscore
noninterestratio_before	-0.006		0.003		0.018***		-5.749***	
	(0.006)		(0.005)		(0.006)		(1.756)	
nonloanasset_before		-0.001		-0.014***		-0.005		3.856**
		(0.004)		(0.003)		(0.005)		(1.676)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
N	109	109	109	109	109	109	109	109
R^2(within)	0.646	0.640	0.701	0.759	0.566	0.529	0.579	0.567
Panel B: COVID-19 pandemic (2020-2022)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ROA_mean	ROA_mean	NIM_mean	NIM_mean	sdROA	sdROA	logzscore	logzscore
noninterestratio_before	-0.002**		-0.009***		0.004***		-5.753***	
	(0.001)		(0.002)		(0.001)		(1.689)	
nonloanasset_before		0.001		-0.004*		-0.002***		2.317
		(0.001)		(0.002)		(0.001)		(1.470)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
N	102	102	102	102	102	102	102	102
R^2(within)	0.647	0.640	0.808	0.787	0.372	0.349	0.283	0.230

Note: This table presents the results for diversification effects during the crisis. Panel A reports the results of the 2008 financial crisis (2007-2009), and Panel B presents the results of the COVID-19 pandemic (2020-2022). The independent variables are noninterestratio_before and nonloanasset_before, which measure the average level of bank diversification in the two years prior to the crisis. For example, in Panel A, noninterestratio_before is measured by the average of the non-interest income ratio in 2005 and 2006. Other control variables (logasset, capitalratio, OHR, fundcost, assetgrowth, NPL, BHC) are included in regressions, but their results are not shown in this table. Specifications include individual, year-fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Figures

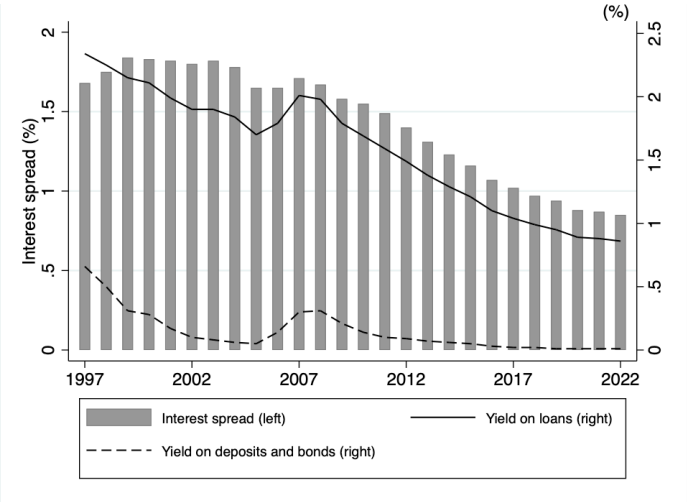

Figure 2-1: Changes in bank's interest spread in Japan
Note: This figure shows the decrease in the bank interest income from 1997 to 2022. Yields on loans are the return from most profitable lending activities, and yields on deposits and bonds measure the cost from a stable funding way. The interest spread is calculated by subtracting the yields on deposits and bonds from yields on loans. All the data are measured at the ordinary banks level, including city banks, regional banks, second regional banks, and trust banks. Detailed data can be found on the official website of the Japanese Bankers Association.

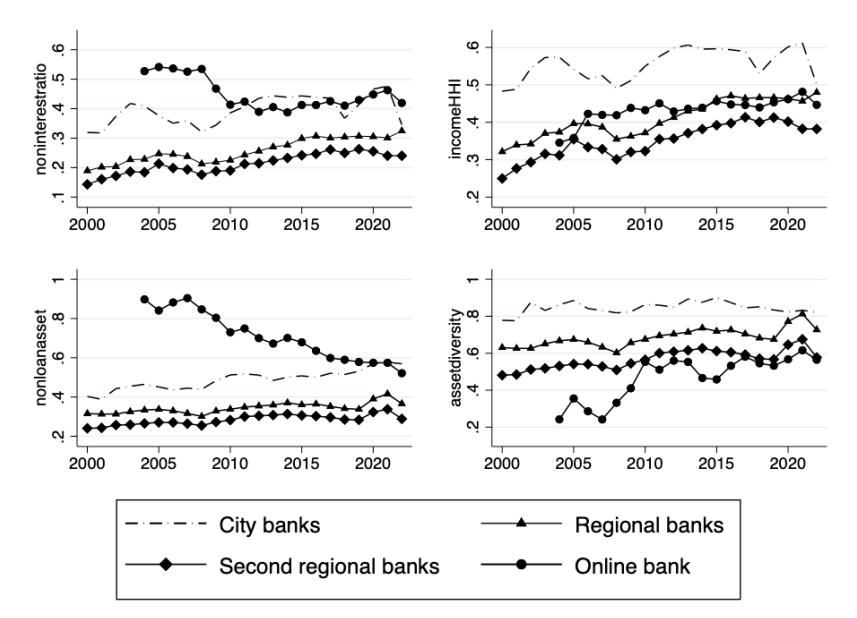

Figure 2-2 Trends in income and asset diversification of different types of banks
Note: This figure shows the average value of diversification for different types of banks in Japan from 2000 to 2022. In general, there are four types of banks in Japan: city bank, regional bank, second regional bank, and online bank. This figure shows a significant increasing trend in income diversification for regional banks and second regional banks, while for city banks, it fluctuated during the past 23 years. However, the changes in asset diversification are relatively flat for all banks.

Appendix

Table A2-1 Endogeneity: IV regressions for 2008 to 2022

	(1) noninterestratio	(2) incomeHHI	(3) l.nonloanasset	(4) l.assetdiversity
Panel A: First-stage within regression				
meandiversification	0.226***	0.181***	0.174***	0.043
	(0.055)	(0.053)	(0.041)	(0.041)
l.diversification	0.456***	0.467***	0.757***	0.695***
	(0.030)	(0.029)	(0.033)	(0.033)
Kleibergen-Paap rk Wald F	151.45	161.48	483.45	200.68
Controls	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	1482	1482	1466	1466
Panel B: Second-stage IV(2SLS) regression				
	(1) ROA	(2) ROA	(3) ROA	(4) ROA
(instrumented)				
noninterestratio	0.004**			
	(0.002)			
incomeHHI		0.004**		
		(0.001)		
l.nonloanasset			0.003**	
			(0.001)	
l.assetdiversity				0.001*
				(0.001)
Hansen J	0.227	0.151	0.886	1.263
Controls	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	1631	1631	2407	2407

Note: This table presents the results controlling for the endogeneity between bank diversification and profitability for 2008 to 2022. The instrumental variables for diversification are the average value of other similar banks' diversification and the one-year lagged diversification variable. In the first-stage regression, the endogenous diversification variable is regressed by the instrument variables and control variables, including logasset, capitalratio, OHR, fundcost, assetgrowth, NPL, BHC, and time fixed effects(results are not shown in this table). In the second-stage regression, the fitted value from the first stage and the same controls are used as explanatory variables. Kleibergen-Paap rk Wald F test and Hansen J test confirm the validity of instrumental variables. Specifications include individual, year-fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table A2-2 Robustness: diversification effects and the 2008 financial crisis

	(1) ROA	(2) ROA	(3) NIM	(4) NIM	(5) sdROA	(6) sdROA	(7) logzscore	(8) logzscore
d_mid×noninterestratio	-0.008		-0.005		-0.004		2.366*	
	(0.008)		(0.004)		(0.005)		(1.326)	
d_post×noninterestratio	-0.001		0.007***		-0.006		1.211	
	(0.002)		(0.003)		(0.004)		(1.103)	
d_mid×l.nonloanasset		-0.006		-0.002		0.002		1.386*
		(0.005)		(0.003)		(0.004)		(0.825)
d_post×l.nonloanasset		-0.001		0.008***		0.002		0.465
		(0.002)		(0.002)		(0.003)		(0.847)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	2689	2548	2689	2548	2407	2407	2407	2407
R^2(within)	0.392	0.400	0.852	0.883	0.330	0.327	0.461	0.461

Note: This table presents the results of the impact of the 2008 financial crisis on diversification effects. The sample is divided into pre-crisis(2000-2006), mid-crisis (2007-2009) and post-2008 financial crisis(2010-2022). d_mid is a dummy variable equal to 1 if the time variable is in the period 2007-209, and d_post is another dummy equal to 1 if the time variable is in the period 2010-2020. Other control variables (logasset, capitalratio, OHR, fundcost, assetgrowth, NPL, BHC) are included in regressions, but their results are not shown in this table. Specifications include individual, year-fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table A2-3 Tests for nonlinear relationships in regional and second regional banks

	(1) ROA	(2) ROA	(3) ROA	(4) ROA	(5) ROA	(6) ROA	(7) sdROA	(8) sdROA	(9) sdROA
noninterestratio	0.024***	0.020**	0.031**						
	(0.006)	(0.008)	(0.012)						
noninterestratiosq	-0.030**	-0.023*	-0.041						
	(0.011)	(0.013)	(0.025)						
l.nonloanasset				0.006	-0.001	0.010	-0.005	-0.001	-0.151
				(0.007)	(0.008)	(0.016)	(0.010)	(0.010)	(0.026)
l.nonloanassetsq				0.006	0.012	0.005	0.003	-0.002	0.019
				(0.011)	(0.011)	(0.027)	(0.013)	(0.013)	(0.040)
Regional banks	YES	YES	NO	YES	YES	NO	YES	YES	NO
Second regional banks	YES	NO	YES	YES	NO	YES	YES	NO	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	2429	1457	972	2306	1385	921	2183	1313	870
R^2(within)	0.418	0.442	0.437	0.422	0.447	0.439	0.326	0.329	0.351

Note: This table presents the results of bank diversification effects only for regional banks and second regional banks. The nonlinear relationship found in baseline regression may be attributed to regressing together with online banks, which have a higher noninterestratio and nonloanasset. To eliminate the possible bias from sample selection, I repeat the baseline regression using only the regional bank sample. Other control variables (logasset, capitalratio, OHR, fundcost, assetgrowth, NPL, BHC) are included in regressions, but their results are not shown in this table. Specifications include individual, year-fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table A2-4 Diversification effects during the crisis: flexible diversification measures

Panel A: the 2008 financial crisis (2007-2009)								
	(1) ROA_mean	(2) ROA_mean	(3) NIM_mean	(4) NIM_mean	(5) sdROA	(6) sdROA	(7) logzscore	(8) logzscore
noninterestratio_mean	0.009*		-0.010		0.005		1.361	
	(0.005)		(0.006)		(0.006)		(1.158)	
nonloanasset_mean		-0.003		-0.014***		-0.001		2.514*
		(0.003)		(0.003)		(0.005)		(1.503)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
N	110	110	110	110	110	110	110	110
R^2(within)	0.649	0.642	0.713	0.764	0.520	0.519	0.543	0.553
Panel B: COVID-19 pandemic (2020-2022)								
	(1) ROA_mean	(2) ROA_mean	(3) NIM_mean	(4) NIM_mean	(5) sdROA	(6) sdROA	(7) logzscore	(8) logzscore
noninterestratio_mean	-0.001		-0.014***		0.003**		-3.086*	
	(0.001)		(0.002)		(0.001)		(1.676)	
nonloanasset_mean		0.002		-0.002		-0.003***		4.419***
		(0.001)		(0.002)		(0.001)		(1.629)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
N	102	102	102	102	102	102	102	102
R^2	0.638	0.643	0.847	0.781	0.358	0.381	0.231	0.272

Note: This table presents the results for diversification effects during the crisis. Panel A reports the results of the 2008 financial crisis (2007-2009), and Panel B presents the results of the COVID-19 pandemic (2020-2022). The independent variables are noninterestratio_mean and nonloanasset_mean, which measure the average level of bank diversification during the crisis. Other control variables (logasset, capitalratio, OHR, fundcost, assetgrowth, NPL, BHC) are included in regressions, but their results are not shown in this table. Specifications include individual, year-fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

References

Abedifar, P., P. Molyneux and A. Tarazi (2018), Non-interest income and bank lending, *Journal of Banking & Finance,* 87**,** 411-26.

Acharya, V. V. and M. Richardson (2009), Causes of the financial crisis, *Critical review,* 21**,** 195-210.

Aggarwal, R. K. and A. A. Samwick (2003), Why do managers diversify their firms? Agency reconsidered, *The Journal of Finance,* 58**,** 71-118.

Ahamed, M. M. (2017), Asset quality, non-interest income, and bank profitability: Evidence from Indian banks, *Economic Modelling,* 63**,** 1-14.

Allen, L. and J. Jagtiani (2000), The risk effects of combining banking, securities, and insurance activities, *Journal of Economics and Business,* 52**,** 485-97.

Ashcraft, A. B. (2008), Are bank holding companies a source of strength to their banking subsidiaries?, *Journal of Money, Credit and Banking,* 40**,** 273-94.

Avraham, D., P. Selvaggi and J. I. Vickery (2012), A structural view of US bank holding companies, *Economic Policy Review,* 18**,** 65-81.

Baele, L., O. De Jonghe and R. V. Vennet (2007), Does the Stock Market Value Bank Diversification, *Journal of Banking & Finance,* 31**,** 1999-2023.

Bellemare, M. F., T. Masaki and T. B. Pepinsky (2017), Lagged explanatory variables and the estimation of causal effect, *The Journal of Politics,* 79**,** 949-63.

Benston, G. J., G. A. Hanweck and D. B. Humphrey (1982), Scale economies in banking: A restructuring and reassessment, *Journal of Money, Credit and Banking,* 14**,** 435-56.

Berger, A. N. and R. Deyoung (1997), Problem loans and cost efficiency in commercial banks, *Journal of Banking & Finance,* 21**,** 849-70.

Berger, A. N., G. A. Hanweck and D. B. Humphrey (1987), Competitive viability in banking: Scale, scope, and product mix economies, *Journal of monetary economics,* 20**,** 501-20.

Berger, A. N., I. Hasan and M. Zhou (2010), The effects of focus versus diversification on bank performance: Evidence from Chinese banks, *Journal of Banking & Finance,* 34**,** 1417-35.

Bhidé, A. (2011), An accident waiting to happen: securities regulation and financial deregulation. What caused the financial crisis. University of Pennsylvania Press.

Brunnermeier, M. K., G. N. Dong and D. Palia (2020), Banks' noninterest income and systemic risk, *The Review of Corporate Finance Studies,* 9**,** 229-55.

Carlson, M., H. Shan and M. Warusawitharana (2013), Capital ratios and bank lending: A matched bank approach, *Journal of Financial Intermediation,* 22**,** 663-87.

Chiorazzo, V., V. D'apice, R. Deyoung and P. Morelli (2018), Is the traditional banking model a survivor?, *Journal of Banking & Finance,* 97**,** 238-56.

Clark, J. A. (1988), Economies of scale and scope at depository financial institutions: A review of the literature, *Federal Reserve Bank of Kansas City Economic Review,* 73**,** 16-33.

Crotty, J. (2009), Structural causes of the global financial crisis: a critical assessment of the 'new financial architecture', *Cambridge journal of economics,* 33**,** 563-80.

De Jonghe, O. (2010), Back to the basics in banking? A micro-analysis of banking system stability, *Journal of Financial Intermediation,* 19**,** 387-417.

Demirgüç-Kunt, A. and H. Huizinga (2010), Bank activity and funding strategies: The impact on risk and returns, *Journal of Financial Economics,* 98**,** 626-50.

Demirguc-Kunt, A., E. Detragiache and O. Merrouche (2013), Bank capital: Lessons from the financial crisis, *Journal of Money, Credit and Banking,* 45**,** 1147-64.

Deyoung, R. and T. Rice (2004a), How do banks make money? The fallacies of fee income, *Economic Perspectives-Federal Reserve Bank of Chicago,* 28**,** 34.

Deyoung, R. and T. Rice (2004b), Noninterest income and financial performance at US commercial banks, *Financial review,* 39**,** 101-27.

Deyoung, R. and K. P. Roland (2001), Product mix and earnings volatility at commercial banks: Evidence from a degree of total leverage model, *Journal of Financial Intermediation,* 10**,** 54-84.

Deyoung, R. and G. Torna (2013), Nontraditional banking activities and bank failures during the financial crisis, *Journal of Financial Intermediation,* 22**,** 397-421.

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

Dormann, C. F., J. Elith, S. Bacher, C. Buchmann, G. Carl, G. Carré, J. R. G. Marquéz, B. Gruber, B. Lafourcade and P. J. Leitão (2013), Collinearity: a review of methods to deal with it and a simulation study evaluating their performance, *Ecography,* 36**,** 27-46.

Elsas, R., A. Hackethal and M. Holzhäuser (2010), The anatomy of bank diversification, *Journal of Banking & Finance,* 34**,** 1274-87.

Elyasiani, E. and Y. Wang (2012), Bank holding company diversification and production efficiency, *Applied Financial Economics,* 22**,** 1409-28.
Filson, D. and S. Olfati (2014), The impacts of Gramm–Leach–Bliley bank diversification on value and risk, *Journal of Banking & Finance,* 41**,** 209-21.
Gambacorta, L. and P. E. Mistrulli (2004), Does bank capital affect lending behavior?, *Journal of Financial Intermediation,* 13**,** 436-57.
García-Herrero, A., S. Gavilá and D. Santabárbara (2009), What explains the low profitability of Chinese banks?, *Journal of Banking & Finance,* 33**,** 2080-92.
Goetz, M. R., L. Laeven and R. Levine (2016), Does the Geographic Expansion of Banks Reduce Risk, *Journal of Financial Economics,* 120**,** 346-62.
Guerry, N. and M. Wallmeier (2017), Valuation of diversified banks: New evidence, *Journal of Banking & Finance,* 80**,** 203-14.
Harris, M., C. H. Kriebel and A. Raviv (1982), Asymmetric information, incentives and intrafirm resource allocation, *Management science,* 28**,** 604-20.
Jensen, M. C. (1986), Agency costs of free cash flow, corporate finance, and takeovers, *The American economic review,* 76**,** 323-29.
Jensen, M. C. and W. H. Meckling (1976), Theory of the firm: Managerial behavior, agency costs and ownership structure, *Journal of Financial Economics,* 3**,** 305-60.
Köhler, M. (2015), Which banks are more risky? The impact of business models on bank stability, *Journal of Financial Stability,* 16**,** 195-212.
Laeven, L. and R. Levine (2007), Is There a Diversification Discount in Financial Conglomerates, *Journal of Financial Economics,* 85**,** 331-67.
Laeven, L. and R. Levine (2009), Bank governance, regulation and risk taking, *Journal of Financial Economics,* 93**,** 259-75.
Lepetit, L., E. Nys, P. Rous and A. Tarazi (2008a), Bank income structure and risk: An empirical analysis of European banks, *Journal of Banking & Finance,* 32**,** 1452-67.
Lepetit, L., E. Nys, P. Rous and A. Tarazi (2008b), The expansion of services in European banking: Implications for loan pricing and interest margins, *Journal of Banking & Finance,* 32**,** 2325-35.
Lewbel, A. (2012), Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models, *Journal of Business & Economic Statistics,* 30**,** 67-80.
Lind, J. T. and H. Mehlum (2010), With or without U? The appropriate test for a U‐shaped relationship, *Oxford bulletin of economics and statistics,* 72**,** 109-18.
Maudos, J. and L. Solís (2009), The determinants of net interest income in the Mexican banking system: An integrated model, *Journal of Banking & Finance,* 33**,** 1920-31.
Mcallister, P. H. and D. Mcmanus (1993), Resolving the scale efficiency puzzle in banking, *Journal of Banking & Finance,* 17**,** 389-405.
Mercieca, S., K. Schaeck and S. Wolfe (2007), Small European banks: Benefits from diversification?, *Journal of Banking & Finance,* 31**,** 1975-98.
Nezu, E. (1999), Transition and Choice of Financial System:The Cases of America,japan and China, *ECONOMIC STUDIES,* 48**,** 455-66.
Nguyen, J. (2012), The relationship between net interest margin and noninterest income using a system estimation approach, *Journal of Banking & Finance,* 36**,** 2429-37.
Nisar, S., K. Peng, S. Wang and B. N. Ashraf (2018), The impact of revenue diversification on bank profitability and stability: Empirical evidence from South Asian countries, *International journal of financial studies,* 6**,** 40.
Rajan, R., H. Servaes and L. Zingales (2000), The cost of diversity: The diversification discount and inefficient investment, *The Journal of Finance,* 55**,** 35-80.
Rogers, K. E. (1998), Nontraditional activities and the efficiency of US commercial banks, *Journal of Banking & Finance,* 22**,** 467-82.
Sanya, S. and S. Wolfe (2011), Can banks in emerging economies benefit from revenue diversification?, *Journal of Financial Services Research,* 40**,** 79-101.
Sawada, M. (2013), How does the stock market value bank diversification? Empirical evidence from Japanese banks, *Pacific-Basin Finance Journal,* 25**,** 40-61.
Schmid, M. M. and I. Walter (2009), Do financial conglomerates create or destroy economic value?, *Journal of Financial Intermediation,* 18**,** 193-216.
Shim, J. (2013), Bank capital buffer and portfolio risk: The influence of business cycle and revenue diversification, *Journal of Banking & Finance,* 37**,** 761-72.
Shrieves, R. E. and D. Dahl (1992), The relationship between risk and capital in commercial banks, *Journal of Banking & Finance,* 16**,** 439-57.
Stein, J. C. (1997), Internal capital markets and the competition for corporate resources, *The Journal of Finance,*

52**,** 111-33.
Stiroh, K. J. (2004), Diversification in banking: Is noninterest income the answer?, *Journal of Money, Credit and Banking***,** 853-82.
Stiroh, K. J. and A. S. Rumble (2006), The Dark Side of Diversification: The Case of US Financial Holding Companies, *Journal of Banking and Finance,* 30**,** 2131-61.
Stulz, R. (1990), Managerial discretion and optimal financing policies, *Journal of Financial Economics,* 26**,** 3-27.
Uchida, H. and G. F. Udell (2014), Banking in Japan. in: Berger, A. N., P. Molyneux and J. O. S. Wilson (eds.) The Oxford handbook of banking. Oxford University Press.
Valverde, S. C. and F. R. Fernández (2007), The determinants of bank margins in European banking, *Journal of Banking & Finance,* 31**,** 2043-63.
Vennet, R. V. (2002), Cost and profit efficiency of financial conglomerates and universal banks in Europe, *Journal of Money, Credit and Banking***,** 254-82.
Wagner, W. (2010), Diversification at financial institutions and systemic crises, *Journal of Financial Intermediation,* 19**,** 373-86.
Williams, B. (2016), The impact of non-interest income on bank risk in Australia, *Journal of Banking & Finance,* 73**,** 16-37.
Wu, J., L. Chen, M. Chen and B. N. Jeon (2020), Diversification, efficiency and risk of banks: Evidence from emerging economies, *Emerging Markets Review,* 45**,** 100720.
Yamori, N., K. Harimaya and K. Kondo (2003), Are banks affiliated with bank holding companies more efficient than independent banks? The recent experience regarding Japanese regional BHCs, *Asia-Pacific Financial Markets,* 10**,** 359-76.
Zhang, J. and E. Malikov (2022), Off-balance sheet activities and scope economies in US banking, *Journal of Banking & Finance,* 141**,** 106534.
Zouaoui, H. and F. Zoghlami (2023), What do we know about the impact of income diversification on bank performance? A systematic literature review, *Journal of Banking Regulation,* 24**,** 286-309.

Chapter 3 Economies of scope in the Japanese banking industry

Abstract: Economies of scope are usually considered a key factor in explaining bank diversification benefits, as joint production can help spread costs across different operations. However, previous studies have yielded little evidence of scope economies in the banking sector, which fails to explain the empirical results of diversification benefits, especially in Japan. Given that most relevant studies were conducted prior to 2000 and newer methodological approaches have emerged to enhance estimation accuracy, we redirect our focus to this topic and explore the relationship with bank diversification. In this paper, we estimate economies of scope while considering the growing off-balance sheet activities within the Japanese banking industry. Using a sample including 120 Japanese banks from 2000 to 2020, we estimate the cost frontier with a translog cost function through the stochastic frontier analysis (SFA) approach. In addition to the traditional measures, we incorporate a new measure of scope economies proposed by Chavas and Kim (2010), allowing us to decompose the scope economies into four different effects. Our findings reveal that a significant portion of Japanese banks demonstrate scope economies, potentially accounting for the observed diversification benefits in Japan. Furthermore, we observe a diminishing trend in scope economies as bank diversification levels increase.

Keywords: Economies of scope; Bank diversification; Japanese bank; SFA

3.1. Introduction

Over the past two decades, researchers have been trying to figure out the diversification effects when banks expand their operations. Statistics show that not only banks in the U.S., Europe, and Japan, but also banks in some emerging markets have become more diversified than in the past (see more from Bolt and Humphrey, 2010, Sawada, 2013, Berger et al., 2010, Nguyen, 2018, DeYoung and Rice, 2004). One reason is that banks are allowed to operate more non-interest-generating businesses, such as securities, insurance, and other off-balance sheet activities, through a universal bank model or a holding company structure. The deregulation and financial innovations encourage banks to adopt a diversification strategy toward a more competitive market. However, this also raised concern about the "too-big-to-fail" (TBTF) problem, especially after the 2008 Global Financial Crisis. The debate about bank diversification is long-standing and has not reached a consensus. The proponents of focused banks cite specialized expertise and less severe agency problem (Jiraporn et al., 2006) as reasons to support the specialization. On the other hand, the proponents of diversification argue that banks can benefit from the economics of scope and synergy effect (Elsas et al., 2010, Zhang and Malikov, 2022), efficient internal market (Stein, 1997), and cooperation with joint ventures (Amici et al., 2013).

Empirical studies also provide inconsistent evidence where both diversification discounts and benefits have been found. The regression results vary due to the difference in countries, periods, and variable measures. For example, Baele et al. (2007) and Chiorazzo et al. (2008) find that diversified banks in the EU have better performance compared with their specialized competitors, while diversification discounts are often found in the U.S. (Laeven and Levine, 2007, Stiroh and Rumble, 2006, Schmid and Walter, 2009, Stiroh, 2004). Even within the same country, the results are often different. Guerry and Wallmeier (2017) find that in the United States, diversification was negatively correlated with bank value before the 2008 financial crisis, but the discounts decreased and eventually vanished to zero after the crisis. One explanation for this problem is that most of the above studies only estimate the net effect of bank diversification (Guerry and Wallmeier, 2017). There may be positive and negative diversification effects due to the complex mechanisms, but we can get only a coefficient that includes all possible effects from regression results. In other words, it is like a black box, and we know little about which factors contribute to the net effect. Therefore, this paper tries to understand the diversification effects from a widely accepted channel, economies of scope in production costs.

In previous studies, researchers consider economies of scope as a main factor contributing to diversification benefits. Economies of scope refer to the propriety of production that firms with multi-production lines can enjoy a cost reduction effect compared with separate production (Panzar and Willig, 1981). For banks, economies of scope can arise from three sources: (1) information sharing. As a financial intermediary, banks have an informational advantage over other market participants and are naturally encouraged to diversify their risk through different operations, which allows banks to save costs. Banks not only collect massive amounts of data from borrowers but also produce information through searching and monitoring, especially private information such as customer data. This valuable information is exclusive but can flow between different businesses of one bank at a very low cost. (2) spreading fixed costs. Unlike manufacturing, banks do not need to invest heavily in fixed assets, and fixed costs can be spread through a broader range of outputs. For example, banks can sell insurance or securities to their customers through the existing branch network. (3) advertising. Banks can save costs on advertising if customers prefer "one-stop banking" due to lower search costs or brand loyalty. Therefore, diversified banks may have higher profitability or be more valued due to economies of scope.

This paper investigates whether there are economies of scope in the Japanese banking industry and whether diversified banks have an advantage in scope economies. we focus on Japanese banks because Japan has a highly bank-intermediated financial system compared with other developed and market-oriented economies, such as the U.S. and UK. The business scope of Japanese banks was strictly regulated before the 1980s. Subsequently, the Financial System Reform in 1996 (also known as the "Japanese Big Bang") that aimed at improving the competitiveness of Japan's financial market began to deregulate the entry of financial intermediaries. For example, banks are allowed to set up a bank holding company (BHC) to engage in other financial-related businesses, such as investment banking and insurance, similar to the deregulation in the U.S. after the Financial Services Modernization Act of 1999. However, not all Japanese banks have adopted an aggressive diversification strategy. According to Guerry and Wallmeier (2017), the mean share of interest income on total operating income for Japanese banks is higher than that of other developed countries, which indicates that most Japanese banks still rely on traditional lending businesses, making it an appropriate sample to study economies of scope as banks begin to engage in other businesses. Therefore, measuring the economies of scope in the Japanese banking industry may provide new evidence to explain the diversification benefits found in Japan (Sawada, 2013).

Using the stochastic frontier analysis (SFA) approach, a translog cost function is estimated with a sample of 120 banks from 2000 to 2020. Specifically, off-balance sheet activities are considered a major output in the cost function as such operations are found to affect banks' profitability and risk (Karim et al., 2013, Calmès and Théoret, 2010). We use two measures to calculate banks' scope economies with the estimated cost function: within-sample scope economies (Mester, 1991) and economies of diversification (Chavas and Kim, 2010). The former can avoid the extrapolation problem, where out-of-sample values are used in predicting costs. The latter is a more generalized form and provides a framework for decomposing the total effect into four different parts: complementarity, scale, convexity, and fixed cost effects, which offers a new perspective on understanding economies of diversification. Further, we investigate whether diversified banks have advantages on scope economies through regression analysis.

Our results provide strong evidence of the existence of scope economies in the Japanese banking industry. The mean values of within-sample scope economies have been significantly positive for different-size banks over the past 21 years. The results show that about 99% of banks exhibit positive scope economies. Similarly, economies of diversification are also found to be positive under different specialization patterns, suggesting that diversified banks can save costs under partial specialization. When referring to the decomposed effects, we find that positive complementarity and scale effects contribute to the economies of diversification. In addition, we find that diversification is negatively linked with scope economies, indicating that being more diversified may not bring more cost-saving benefits. These results are robust since robust checks yield similar results. Overall, our results support that Japanese banks have economies of scope, which may explain the bank diversification benefits found in Japan.

This study contributes to the literature in three ways. First, we add new evidence on the economies of scope in the Japanese banking industry by using recent data. Previous studies in Japan focus on the 1990s and ignore the growth of off-balance sheet activities, which is somewhat outdated. Our study estimates banks' economies of scope in Japan and provides new evidence about the existence of scope economies in the context of more banks expanding their off-balance sheet operations. Second, to our knowledge, this study is the first to use the measure of economies of diversification in banking. Based on the framework introduced by Chavas and Kim (2010), we first estimate the economies of diversification of Japanese banks and their decomposed effects. Furthermore, we also decompose within-sample scope economies under the same framework, which extends the application of this framework. Third, unlike the previous studies, we calculate the scope economies at the bank level rather than at the banking

sector level, which enables us to analyze the factor that may affect scope economies. Since most studies consider scope economies as a main factor contributing to bank diversification benefits, we focus on the relationship between the level of bank diversification and economies of scope. Our study enriches the literature not only in the estimations of scope economies but generates new insights regarding the mechanism of bank diversification.

The paper is organized as follows: Section 2 reviews the literature on the estimation of scope economies. Section 3 describes the methodology and data. Section 4 presents the estimation and regression results, and robustness checks are shown in Section 5. Section 6 concludes.

3.2. Literature review

The estimation studies of economies of scope in banking began in the 1980s. Benston et al. (1983), Murray and White (1983), Gilligan et al. (1984), Gilligan and Smirlock (1984), Kim (1986), Berger et al. (1987), Mester (1987) develop the early research on this topic. Clark (1988) reviews 13 initial studies on estimating the economies of scale and scope for depository financial institutions. The results show that most studies did not find consistent and significant evidence that economies of scope exist in the U.S. or Canadian market. They only find some cost complementarities between pairs of products, such as investments and loans (Gilligan and Smirlock, 1984), and deposits and loans (Gilligan et al., 1984, Berger et al., 1987). More empirical evidence has been provided as more researchers focus on this topic, but the results vary from paper to paper.

Most previous studies on economies of scope have focused on improving estimation methods to obtain more precise estimates. First, the variable selection of banks' inputs and outputs has become more flexible since the production of banking is becoming more complex due to deregulation and financial innovation. Banks' off-balance sheet activities (Jagtiani et al., 1995, Berger and Mester, 1997, Clark and Siems, 2002, Rogers, 1998) and the quality of bank assets (Mester, 1996) are considered to be the vital variables in the cost function. Jagtiani et al. (1995) find cost complementarity between aggregate OBS items and earning assets with a sample of 134 banks in the United States. Zhang and Malikov (2022) argue that today's product portfolios offered by banks are quite different from two decades ago. They examine whether these changes alter the previous findings that there are no economies of scope or slight diseconomies of scope in the U.S. banking industry. Through a flexible time-varying-coefficient panel-data quantile regression model with a sample for the U.S. commercial banks from 2009 to 2018, they find strong evidence that economies of scope exist for all sizes of banks. Second, more

general functional forms of the cost function have been employed to approximate the true cost function, such as the hybrid translog function (Mester, 1992, Noulas et al., 1993), the composite cost function (Pulley and Braunstein, 1992, Pulley and Humphrey, 1993), and the Fourier Flexible cost equation (Mitchell and Onvural, 1996). However, only Pulley and Braunstein (1992), and Pulley and Humphrey (1993) find significant economies of scope in the U.S. banking sector. Further, semiparametric and nonparametric approaches have gained popularity in recent years, particularly in bank efficiency estimation, as they allow for greater flexibility in relaxing the assumption regarding the functional form. Wheelock and Wilson (2001) compare the scope economies results estimated by parametric and nonparametric methods and find that the results are similar in sign but different in quantities. Third, the definition and measure of scope economies become more diverse. Except for the traditional definition proposed by Panzar and Willig (1981) and Baumol et al. (1982), the cost complementarities between different outputs (Jagtiani et al., 1995), Expansion Path Subadditivity (EPSUB) (Berger et al., 1987, Wheelock and Wilson, 2001), Grid Subadditivity (GRIDSUB) (Hunter et al., 1990) are used to measure a similar cost-saving effect from joint production. In addition, instead of the cost-saving perspective, Berger et al. (1996) estimate a revenue function and calculate revenue economies of scope, which measures revenue earning effects from joint production. Their results suggest no significant revenue economies of scope for either small or large U.S. banks over 1978-1990. In contrast, Abedifar et al. (2018) find profit complementarity between loans and non-interest activities for medium-sized U.S. banks between 2007 to 2016.

When it comes to the drivers of economies of scope, most studies argue that bank size has a vital effect. Noulas et al. (1993) find that economies of scope exist only for relatively small-sized U.S. banks, and it becomes diseconomies if assets exceed 6 billion. Similarly, Wheelock and Wilson (2001) show that the positive EPSUB appears to diminish with increasing bank size. A recent study conducted by Malikov and Hartarska (2018) also shows that small-sized microfinance institutions in the United States are more likely to exhibit scope economies. This negative relationship is also confirmed by the non-U.S. banks. Altunbas and Molyneux (1996) estimate economies of scope in 4 European countries and show that significant scope economies are found only in Spanish small-size banks. In contrast, Cavallo and Rossi (2001) find that scope economies are more pronounced for larger banks in six European countries from 1992-1997. Beccalli and Rossi (2020) examine cost, revenue, and profit economies of scope with a large sample including 28 European countries from 2005-2018. They find significant cost economies of scope in the EU banking sector and a U-shaped relationship with

bank size, indicating small and large-sized banks can enjoy greater scope economies. What is more, Vennet (2002) argues that bank type affects the relationship between size and scope economies. Using the sample of 17 European countries from 1995-1996, he finds that small-sized specialized banks can enjoy economies of scope, while large financial conglomerates and universal banks have more pronounced economies of scope. In addition to bank size, riskiness of the lending activity (Malikov and Hartarska, 2018), and liquid assets (Beccalli and Rossi, 2020) are also found to affect scope economies.

In short, the literature on estimating economies of scope and drivers of economies of scope in banking sector is limited. Prior literature does not provide consistent evidence to validate the existence of economies of scope or diseconomies of scope in banking. On the other hand, as noted by Zhang and Malikov (2022), prior studies concentrate on the 1980s and 1990s and may be outdated due to the dramatic changes in non-traditional bank businesses, but few studies have shed light on these changes. Moreover, recent related studies provide new evidence of economies of scope in the U.S. or EU, calling for more research on this topic.

3.3. Methodology and data

Generally, there are three steps to estimating economies of scope in the Japanese banking industry. Firstly, choose proper outputs, inputs, and price variables to describe the production of a bank. Then, estimate banks' cost function no matter by parametric or nonparametric methods. At last, calculate the economies of scope with the definitional equations and the estimated cost function.

3.3.1 Outputs, inputs, and price variables

To specify the inputs and outputs of bank production, there are two main approaches: production and intermediation approaches, which are discussed in detail in Humphrey (1985). The main difference is how to treat deposits. The "intermediation approach" proposed by Sealey Jr and Lindley (1977) views banks as intermediation service providers and therefore deposits are considered as inputs rather than outputs for banks in the production approach. In this paper, we focus on the banks' intermediate function as in most recent studies. Following the "intermediation approach", bank outputs are defined as follows: the first output (Y_1) is banks' loans, consisting of all kinds of loans and bills discounted in the balance sheet; Y_2 is the securities held by banks. It includes both securities held-to-maturity and securities held-for-sale, which are also used in Zhang and Malikov (2022); Y_3 is the off-balance sheet (OBS) activities, which measures banks' nontraditional operations. Some studies use net non-interest

income as a proxy of the OBS operations (Lozano-Vivas and Pasiouras, 2010, Clark and Siems, 2002, Wheelock and Wilson, 2012, Davies and Tracey, 2014). However, this measure suffers from the negative value problem, making it undesirable for outputs. What is more, as argued by Zhang and Malikov (2022), it has a fundamental conceptual incongruity with other outputs because it is based on flow (income) data rather than stock (asset) data. Therefore, other researchers prefer to use nominal values or credit-equivalent amounts of the OBS activities collected from banks' financial statements or other public reports, such as the FR Y-9C or FFIEC 041 Reports in the U.S. (see more in Lozano-Vivas and Pasiouras, 2010, Lozano-Vivas and Pasiouras, 2014, McCord and Prescott, 2014, Beccalli et al., 2015, Zhang and Malikov, 2022, Hughes and Mester, 2013). Unfortunately, Japan has no specified related reports due to a different accounting and regulatory system. To address this issue, I attempt to compare the OBS items in Japanese bank financial statements with previous literature and use the summation of the nominal values of acceptances and guarantees, unused commitment lines, and derivatives[15] to measure the Japanese banks' OBS activities. Still, net non-interest income will be used as an alternative measure of Y_3 in the robustness checks.

The three inputs are deposits and borrowings (X_1), labor (X_2), and physical capital (X_3). The prices for the inputs are calculated as follows: the price of deposits and borrowings (P_1) is calculated by dividing interest expenses on deposits, negotiable certificates of deposit and borrowings by the sum of deposits, negotiable certificates of deposit and borrowings; the price of labor (P_2) is measured as the average annual salary of bank employees; the price of physical capital (P_3) is computed by dividing the difference between ordinary expenses and labor expenses[16] by fixed assets. In addition to the above conventional inputs, a quasi-fixed input, equity capital (E), and the time variable (T) are also introduced. As discussed in Mester (1996), Berger and Mester (2003), and Hughes and Mester (2013), equity capital can directly affect banks' costs because managers can choose a high-risk strategy with a more aggressive capital structure when facing less valuable investment opportunities, which may affect the costs paid for other inputs. Moreover, equity capital is also a source of loanable funds for banks and can be used as a cushion against losses and insolvency. It is also important to note that equity capital is a quasi-fixed input because it does not change rapidly, and it is difficult to measure the price of equity capital, which leaves no price variable for equity capital in the cost function.

[15] Depravities are calculated as the financial derivatives in the asset part of a bank's balance sheet. If banks are allowed to set up a special trading account, trading securities derivatives, trading account securities derivatives for hedging, and trading account financial derivatives are also included.

16 Labor expenses are equal to the average annual salary of bank employees multiplied by the number of bank employees.

The time variable (T) acts as a factor reflecting technical changes during the sample periods (see more in Lozano-Vivas and Pasiouras, 2010, Gaganis and Pasiouras, 2013, Feng and Zhang, 2014). T is set as an ordered categorical variable but treated as a continuous variable (Wheelock and Wilson, 2012). Adding a time variable can allow more flexibility in the cost function, as the economic environment and the production technology may have changed considerably, especially for a long sample period. With all these variables defined, the total cost equals the sum of expenses on deposits, negotiable certificates of deposit and borrowings, and general and administrative expenses.

3.3.2 Cost function and estimation

In previous literature, both parametric and nonparametric cost functions have been used to estimate bank costs. The former needs to specify a functional form first, such as translog or quadratic function, which always suffers from the risk of misspecification due to the unavailability of the true functional form. In contrast, the latter can avoid the specification error because of no requirement for the specific functional form. However, estimating a nonparametric cost function is much more difficult and complex. As argued by Wheelock and Wilson (2012), nonparametric estimators are subject to the "curse of dimensionality", which means that the number of variables will affect the efficiency of the estimation. Despite using the principal components technique to reduce the dimensions, they still lose some information after the transformation. In addition, a large sample is another precondition for estimation due to the slow convergence rates of nonparametric estimators. It seems to be a trade-off between accuracy and efficiency. Therefore, considering the limited bank sample size in Japan, I employ stochastic frontier analysis to estimate a conventional translog cost function in the main analysis and a semiparametric function, the Fourier Flexible (FF) cost function, in robustness checks. Following Greene (2005a) and Greene (2005b),the translog cost function is set as:

$$\ln\frac{C_{it}}{P_3} = \alpha_i + \sum_{m=1}^{3}\alpha_m \ln Y_{m,it} + \sum_{k=1}^{2}\beta_k \ln\frac{P_{k,it}}{P_3} + \gamma_0 \ln E_{it} + \delta_0 T + \sum_{m=1}^{3}\sum_{n=1}^{3}\alpha_{mn} \ln Y_{m,it} \ln Y_{n,it} + \sum_{k=1}^{2}\sum_{l=1}^{2}\beta_{kl} \ln\frac{P_{k,it}}{P_3} \ln\frac{P_{l,it}}{P_3} + \gamma_{00} \ln E_{it}^2 + \delta_{00} T^2 + \sum_{m=1}^{3}\sum_{k=1}^{2}\gamma_{mk} \ln P_{m,it} \ln\frac{P_{l,it}}{P_3} + \sum_{m=1}^{3}\gamma_m \ln Y_{m,it} \ln E_{it} + \sum_{m=1}^{3}\delta_m \ln Y_{m,it}\, T + \sum_{k=1}^{2}\theta_k \ln\frac{P_{k,it}}{P_3} \ln E_{it} + \sum_{k=1}^{2}\mu_k \ln\frac{P_{k,it}}{P_3} T + \varphi_0 \ln E_{it}\, T + \mu_{it} + \nu_{it} \quad (1)$$

Where C, Y, P, E, and T denote total costs, outputs, price of inputs, equity capital, and time variable, respectively. The subscripts i and t denote the bank and time index. α_i is the unobserved individual heterogeneity and u_{it}+v_{it} is the composite error term ε_{it}. In addition, theoretical regulatory conditions that ensure the basic properties of a cost function are also satisfied in the regression functions. For example, linear homogeneity requires a change in all input prices would yield the same proportionate change in total cost as suggested by microeconomic theory. This can be easily achieved by dividing the total cost and price terms by the third input price and imposing the symmetry restriction ($\alpha_{mn} = \alpha_{mn}$, $\beta_{kl} = \beta_{lk}$). However, it is still a challenging problem to impose monotonicity and concavity conditions during estimation. Some studies attempt to check these conditions after estimation to justify the estimated cost function, but such checks cannot guarantee that all conditions are satisfied globally. Moreover, with the normalization operation to satisfy linear homogeneity, it becomes harder to impose or check monotonicity and concavity conditions on price variables.

As for the estimation, stochastic frontier analysis introduced by Aigner et al. (1977) is often used to estimate a parametric function. They divide the error term into two parts: u and v, where u captures the level of the bank's technical inefficiency and v denotes the statistical noise. This approach is preferred because, unlike other economic models, it does not assume whether the decision-making units are fully efficient or not, but constructs a data-determined efficiency model, which makes more sense in empirical studies. This treatment makes a natural compromise between two strong assumptions about the deviation, one regarding it as pure statistical noise and the other as a total inefficiency to the frontier (Kumbhakar et al., 2020). For example, the Seemingly Unrelated Regression (SUR) approach that was widely used in the

past to estimate cost function and factor share equations jointly has become less attractive. There is no inefficiency-related term in the cost function, and the factor share equations assume no allocative inefficiency in productivity.

Further, we want to separate bank heterogeneity from the inefficiency term. The time-invariant component can be considered as either persistent inefficiency or individual heterogeneity that has nothing to do with inefficiency. We prefer to view it as bank heterogeneity, as it can partly reflect differences in production endowments. We employ the "true fixed effects" panel stochastic frontier model proposed by Greene (2005a) to estimate the cost function. The method is straightforward, using firm dummy variables to estimate α_i. However, it encounters two challenges: incidental parameters problem and no closed form likelihood function. The former can be mitigated when T is relatively larger (e.g. > 10, Greene (2005b)). For the latter, there is no satisfactory solution at this stage. Even though some researchers have proposed some solutions, these methods lead to a more difficult estimation of α_i (see more on Chen et al., 2014, Wang and Ho, 2010, Belotti and Ilardi, 2018). Finally, assumptions need to be made regarding u, the inefficiency term. The specification of u can be tailored to the focus of the analysis. In this paper, u is constrained to follow a truncated normal distribution as our concern does not extend to the scoring or determinants of banks' inefficiency.

3.3.3 Measures for economies of scope

Economies of scope refer to a cost reduction effect when firms produce multiple products jointly rather than separately by different specialized firms. According to the conventional definition discussed by Panzar and Willig (1981) and Baumol et al. (1982), for banks that produce three outputs, economies of scope can be calculated as:

$$economoies\ of\ scope = \frac{C(Y_1, 0,0) + C(0, Y_2, 0) + C(0,0, Y_3) - C(Y_1, Y_2, Y_3)}{C(Y_1, Y_2, Y_3)} \qquad (2)$$

where C(.) is the cost function of banks. Banks can enjoy the cost-saving effect of engaging in non-traditional operations if economies of scope are positive. In contrast, negative economies of scope indicate diseconomies of scope, implying that specialized banks incur lower costs through separate production compared to diversified banks' joint production. In other words, diversification cannot help banks save costs, and the theory of economies of scope may not explain why banks are eager to be diversified.

While this equation is the theoretical measure of scope economies, it is less realistic and

practical in empirical studies. This is because a translog cost function is often used, making zero output no sense in the logarithmic form. Although researchers have provided some solutions to the zero-output problem, such as substituting an arbitrarily small positive value for zero output or employing Box-Cox transformation, it does not solve the "excessive extrapolation" problem and may introduce unknown bias. It requires the counterfactual bank to produce at a zero or near zero level, even though all banks in the sample do not have such a small output, which makes the estimation involves potentially excessive extrapolation outside the sample (Hughes and Mester, 1993). Therefore, we employ a similar but more reasonable measure proposed by Mester (1991) to measure scope economies. It is calculated as:

$$within - sample\ scope\ economoies = \frac{C(Y_1 - 2Y_{1min}, Y_{2min}, Y_{3min}) + C(Y_{1min}, Y_2 - 2Y_{2min}, Y_{3min}) + C(Y_{1min}, Y_{2min}, Y_3 - 2Y_{3min}) - C(Y_1, Y_2, Y_3)}{C(Y_1, Y_2, Y_3)} \quad (3)$$

where y_{imin} is the minimum value of the ith output in the sample. In contrast to the conventional measure, within-sample scope economies replace zero outputs with the minimum value in the sample and subtract the corresponding extra outputs in relatively specialized banks to make the total output equal to that of a diversified bank. Therefore, this treatment can avoid the problems discussed above and is widely used in subsequent studies (Mitchell and Onvural, 1996, Beccalli and Rossi, 2020, Berger et al., 2010, Zhang and Malikov, 2022, Hughes and Mester, 1993). However, the cost is the loss of some point estimates for the relatively specialized banks whose output is less than two times the minimum value[17]. In a nutshell, within-sample scope economies are constructed on the conventional measure, and similarly, it indicates economies of scope if the value is positive.

Except for economies of scope, we also calculate a new measure, economies of diversification. Chavas and Kim (2010) provide a framework to explain why and how to calculate economies of diversification and, more importantly, the decomposition of economies of diversification. Unlike the conventional measure focusing on complete specialization, economies of diversification reflect the benefits of multi-product production from a partial specialization perspective. This is meaningful because most commercial banks in Japan are somehow diversified. They try to measure whether banks can still benefit from reorganizing production in a more specialized way, which is similar to the within-sample scope economies but with a

[17] In fact, the output needs to be greater than three times the minimum value because the subtracted output should also be greater than the minimum value.

different meaning. The equation to calculate economies of diversification is,

$$S = \left(\sum_{k=1}^{K} C(\boldsymbol{Y}^k, \boldsymbol{P}) - C(\boldsymbol{Y}, \boldsymbol{P}) \right) / C(\boldsymbol{Y}, \boldsymbol{P}) \quad (4)$$

where $\mathbf{Y}^k=\{Y_1^k, Y_2^k, \ldots, Y_m^k\}$ denotes the outputs produced by the kth specialized firm, and $C(\mathbf{Y}^k, \mathbf{P})$ is the minimal cost for this firm to produce $\mathbf{Y}^k$ in a market with K specialized firms and m kinds of outputs ($2 \leq K \leq m$). To match the total outputs of the diversified firm, the outputs $\mathbf{Y}^k$ are restricted to satisfy $\sum_{k=1}^{K} \boldsymbol{Y}^k = \boldsymbol{Y}$. The sigh and magnitude of S depend on the cost function and $\mathbf{Y}^k$, which indicates the pattern of specialization for each output. The pattern of specialization is discussed in Chavas and Kim (2010) in detail, and we employ a simple model similar to Eder (2018) to illustrate how to calculate economies of diversification in the Japanese banking industry.

Following Eder (2018), the market is set up as having three counterfactual specialized banks, each focusing on one of three outputs (K=m=3). The specialization level for each bank is defined by $\boldsymbol{\beta} = (\beta_1, \beta_2, \beta_3)$, where β_k (k=1,2,3) measures the proportion of the specialized output produced by the kth specialized bank relatively to the original output. The remaining output is produced equally by other non-specialized banks. For example, suppose that Bank 1 is specialized in output 1, so Bank produce $\beta_1 Y_1$ and other banks equally produce $[(1-\beta_1)/2]Y_1$. The production in outputs 2 and 3 for Bank 1 then depends on the specialization level of Bank 2 (β_2) and Bank 3 (β_3). Therefore, the larger the β_k ($\beta_k \in (1/3,1]$)[18] is, the more specialized the bank is. When $\beta_k = 1$, it implies that the kth bank is completely specialized, and two other banks do not produce the output that the kth bank specializes in. It is easy to see that the conventional measure of economies of scope is a special case of economies of diversification when $\boldsymbol{\beta} = \mathbf{1}$. Under these settings, economies of diversification are calculated as:

$$\text{economies of diversification} = \frac{C\left(\beta_1 Y_1, \frac{1-\beta_2}{2} Y_2, \frac{1-\beta_3}{2} Y_3\right) + C\left(\frac{1-\beta_1}{2} Y_1, \beta_2 Y_2, \frac{1-\beta_3}{2} Y_3\right) + C\left(\frac{1-\beta_1}{2} Y_1, \frac{1-\beta_2}{2} Y_2, \beta_3 Y_3\right) - C(Y_1, Y_2, Y_3)}{C(Y_1, Y_2, Y_3)} \quad (5)$$

[18] $\beta_k \in (1/K, 1]$, where k is the number of firms. In the paper, K is equal to 3.

Similarly, the positive (negative) sign reflects economies (diseconomies) of diversification, implying the cost of integrated production is lower (greater) than specialization.

A key advantage of economies of diversification is that they can be decomposed into different effects, which provides more insights into understanding diversification. According to Chavas and Kim (2010), the sources of diversification benefits are as follows:

$$S = S_c + S_R + S_V + S_f \tag{6}$$

The term S_C reflects the complementarity effect among different outputs. If S_C is positive, it means that complementarity defined by Baumol et al. (1982) exists, or to be more specific, the increase of some outputs will reduce the marginal cost of other outputs. The term S_R is scale effects, which measures returns to scale. The scale effect is calculated as:

$$S_R = [3C(Y_1/3, Y/3, Y_3/3) - C(Y_1, Y_2, Y_3)]/C(Y_1, Y_2, Y_3) \tag{7}$$

Supposing that three smaller banks have the same diversification level as the larger original bank by equally producing (1/3)***Y**, S_R is positive when the production technology exhibits increasing returns to scale (IRTS). This is because the ray-average cost, $[C(\alpha \boldsymbol{Y}, \boldsymbol{P})/\alpha)]$, is decreasing in α when the technology is IRTS (Baumol et al., 1982). Thus, given $\alpha = 1/3 < 1$, the corresponding ray-average cost, $[3C(\boldsymbol{Y}/3, \boldsymbol{P})]$, is greater than the $C(\boldsymbol{Y}, \boldsymbol{P})$ for $\alpha = 1$. Conversely, S_R is negative or equal to zero under decreasing returns to scale (DRTS) or constant returns to scale (CRTS). The term S_V is called convexity effects, capturing the convexity or concavity property of the cost function in the output **Y**. The convexity effect can be calculated as:

$$S_v = [C(\beta_1 Y_1, \beta_2 Y_2, \beta_3 Y_3) + 2C\left(\frac{1-\beta_1}{2} Y_1, \frac{1-\beta_2}{2} Y_2, \frac{1-\beta_3}{2} Y_3\right) - 3C\left(\frac{Y_1}{3}, \frac{Y_2}{3}, \frac{Y_3}{3}\right)]/C(Y_1, Y_2, Y_3) \tag{8}$$

According to Baumol et al. (1982), if the cost function is trans-ray convex at **Y**, for any combination of two output vectors lying on the same hyperplane, we have $C(k\mathbf{Y}^a+(1-k)\mathbf{Y}^b) \leq kC(\mathbf{Y}^a)+(1-k)C(\mathbf{Y}^b)$ for any k,0<k<1. It is easy to derivate that the convexity effect is positive when the cost function is convex. The economic meaning of trans-ray convex is that marginal costs tend to increase with outputs along with the hyperplane defined by two outputs vectors. Alternatively, if the cost function is concave (linear) in **Y**, the convexity effects are negative

(zero), indicating decreasing (constant) marginal costs. The last term S_f reflects the effects of fixed costs on diversification economies. When there is no fixed cost, the fixed cost effect S_f is equal to zero. However, S_f can be positive, native, or zero if the fixed cost exists. In particular, Chavas and Kim (2010) have proved that $S_f=0$ under partial specialization. This proposition provides a convenient way to measure the complementarity effect S_c because the formula to calculate S_c directly is much more complicated. Specifically, since economies of diversification are considered to arise from the complementarity effect S_c, scale effect S_R, and convexity effect S_v, S_c can be calculated by subtracting S_R and S_v from economies of diversification. The derivation of decomposition and proposition is available in Appendix 1.

3.3.4 Data

The sample used in this paper includes 2083 bank-year observations from 2000 to 2020. As we focus on the commercial banks in Japan, it includes city banks, regional banks, second regional banks, and two transformed Long-Term Credit Banks (LTCB), namely Shinsei Bank and Aozora Bank[19]. Bank holding companies are excluded from the sample, while their bank subsidiaries are included, mainly because labor price data for the entire group are unavailable.

Most bank-level data are collected from Nikkei NEEDS FinancialQuest, a famous database in Japan. We also manually collect some items from banks' annual securities reports, such as the unused commitment lines and the average annual salary of bank employees. Given that many banks operate through various subsidiaries, we utilize data from consolidated financial statements. However, if a bank has no subsidiaries or consolidated data is not available, non-consolidated data is also accepted.

To make the regression results more reliable, we process the collected data in three ways. First, we exclude banks with fewer than 5 years of observations. Such banks may have undergone mergers after the "Japanese Big Bang" in the early 21st century, or they may be newly established entities. In either scenario, the limited observation period fails to capture regular production, potentially introducing unknown biases in the regressions. Second, the merged bank is treated as a new bank. The number of banks mentioned above has declined by 20% over the past 20 years, indicating a significant trend of bank consolidation in Japan. In order to control the effects of mergers, the new bank after the merger is considered a new bank with a different ID. Third, all nominal variables are deflated using the GDP deflator index, collected

[19] Shinsei Bank and Aozora Bank used to be Long-Term Credit Banks and transformed into normal commercial banks in 2004 and 2006, respectively. The observations of these two banks are only accepted after their transformation.

from the Statistics Bureau of Japan and defined as 100 in 2015. Table 3-1 shows summary statistics for the main variables.

As shown in Table 3-1, off-balance sheet activities are also an important part of bank outputs. Although the minimum value of Y_3 is only 1633 million yen, significantly smaller than that of the other two outputs, its mean value is greater than total securities and exceeds half of the loans, which is often overlooked in other Japanese banking studies. In addition, we use the ratio of loans to total outputs to measure the extent to which banks engage in the traditional lending business. This is similar to the asset diversification measure in Laeven and Levine (2007). Figure 3-1 plots the average output share of loans for three main types of commercial banks in Japan from 2000 to 2020. There is a slight downward trend for all types of banks until 2014, followed by a slight rebound, but except for regional banks, the average value is still smaller than that in 2000. This change indicates that despite banks' increased focus on non-traditional businesses, the lending business continues to hold a pivotal position in their operations. On the other hand, this figure also shows considerable heterogeneity across different types of banks, with city banks being the most asset-diversified and regional banks taking second place, as anticipated.

3.4. Results

3.4.1 Estimates of economies of scope

We use the SFA approach to estimate the cost function of Japanese banks and calculate the with-sample scope economies from the equation discussed in Section 3.3.3. In contrast to previous literature, we estimate the economies of scope for individual banks each year. Instead of using the mean values of output, input prices, and equity, we use the original values of these variables for each bank. This approach provides a more precise estimate of whether economies of scope exist for each bank, as all variables reflect the actual operating conditions of that institution. However, it may cause additional uncertainty in the point estimation due to the approximation limits of the translog function.

Table 3-2 summarizes the point estimates results of within-sample scope economies for each year. Column 6 shows the percentage of banks with positive economies of scope, and columns 7 to 10 report the average of scope economies for four groups divided by bank assets from small to large. The mean values of banks' within-sample scope economies from 2000 to 2020 are all positive and statistically significant at the 99% confidence level, as demonstrated by t-tests. It indicates that economies of scope exist in the Japanese banking industry, where the

total cost of three counterfactual specialized banks is, on average, 0.549 times higher than that of a diversified bank producing the same outputs. Even though the minimum value shows that not all banks have economies of scope, the mean percentage in column 6 indicates that about 99.14% of bank-year observations are positive in scope economies. This also supports that most banks in Japan can enjoy economies of scope. In addition, to investigate whether economies of scope differ across bank sizes, we categorize banks into four groups based on total assets each year, with Group 1 comprising the smallest banks. The average estimates for each group suggest a possible negative relationship between scope economies and bank assets: small-sized banks may experience larger economies of scope than large banks. This is justified in Table 3-3, which reports the differences in scope economies between every two groups by a t-test. The difference in average scope economies is positively significant between Groups 1, 2, and Groups 3, 4, while insignificant between Groups 3 and 4. This result is consistent with most previous studies in the U.S., as discussed in the literature review. It is also important to note that it may be too arbitrary to say that bank size has a direct effect on economies of scope because bank assets are not introduced as a factor in the regression model and the calculation of scope economies. In other words, bank size may be related to the quantity of output and somewhat reflects the characteristics of the estimated cost function.

On the other hand, our findings reveal a noticeable upward trend in the average level of scope economies over the past 21 years. As illustrated in Figure 3-2, the mean value of scope economies has increased from 0.276 in 2000 to 0.963 in 2020, particularly after 2009, exhibiting a significant surge across all groups. This upward trend may indicate significant technological changes in bank productivity over the years. Specifically, joint production has become less expensive, enabling banks to achieve greater savings from scope extension compared to the past. For instance, in 2000, approximately 94.81% of banks benefitted from economies of scope, while after 2008, this share rose to 100%. This could be attributed to the adoption and advancement of new information technology in bank operations, such as Internet banking and Fintech. Humphrey et al. (2006) show that the adoption of electronic payments and the widespread use of ATMs in Europe have led to savings equivalent to 0.38% of GDP in bank operating costs, highlighting the significant impact of technological change on banking expenditures. With more new technology adopted, it can increase the efficiency of employees since they can deal with several businesses with simple training. Also, applied information technology can be shared among different departures, making it more efficiency to spread the cost among different products. More importantly, online banking has made it easier and faster

to provide multiple services to the same customer than in the past, thereby reducing search costs for both parties.

Furthermore, the variations in the mean value of the four groups provide additional insights. While we find that banks of different sizes differ in the degree of economies of scope, Figure 3-2 reveals that this divergence decreases significantly after 2013. The different attitudes toward technology can partially explain this result. As large banks are more likely to adopt new technology, it is anticipated that the increasing trend will be more pronounced than that of small banks.

3.4.2 Estimates of economies of diversification

Unlike economies of scope, economies of diversification measure the cost difference between a diversified bank and partially specialized banks. The specialization pattern is determined by the subjectively chosen parameter, β, ranging from 1/K to 1, where K is the number of specialized banks (K=3 in this paper). While a higher β means closer to conventional economies of scope, it will also lead to more severe extrapolation problems. Therefore, following Eder (2018), we also choose three specialization patterns, $\beta_1 = \beta_2 = \beta_3 = 0.9, 0.8, 0.7$. In addition, it is easy to deduce that economies of diversification are equal to within-sample scope economies when

$$\beta_{i,k} = 1 - \frac{2Y_{min,k}}{Y_{i,k}} \tag{9}$$

is satisfied, where i denotes the bank-year index and k=1,2,3. It means that $\boldsymbol{\beta}$ varies in every bank-year observation. Similarly, all variables in the calculation use their original value, as discussed above.

Table 3-4 shows the mean value of economies of diversification and three decomposition effects in each year under different partial specialization patterns. The average economies of diversification are all positive and significant at the 99% confidence level for three different partial diversification patterns. For example, for β =0.8, where the specialized banks produce 10% of the original outputs in the other two outputs, the total costs of three counterfactual banks are, on average, as much as 1.689 times higher than that of a diversified bank. These results indicate that a more diversified bank still has cost-saving benefits even under partial specialization. Moreover, the decomposition effects generate more information about the source of economies of diversification. We find that positive complementarity and scale effects

contribute to the economies of diversification, whereas the convexity effects are negative.

The positive complementarity effect implies that the marginal cost of one output decreases with the increase of other outputs, suggesting that the costs of diversified banks increase more slowly when they engage in non-traditional bank businesses. Our results partly contradict the findings of Harimaya (2008), who found a significant cost anticomplementarity between lending and securities businesses for Japanese regional banks. However, it is important to note that the complementarity effect in this paper is not estimated for individual combinations but represents a total effect encompassing all pairwise combinations. Furthermore, we find that with the decline of specialization patterns, the complementarity effect also decreases. For example, the mean value of the complementarity effect is 0.225 when β=0.9, but it decreases to 0.113 and 0.061 at β=0.8 and 0.7, respectively. This means banks benefit less from the complementarity effect of integration if they want to be more diversified. On the other hand, the scale effect does not vary with β since it maintains the same proportion among the three outputs as the original output vector. In terms of magnitude, the positive scale effect dominates the total effect, DIV, especially when β is small. We find that the scale effect is even larger than the total effect. These results suggest that the cost-saving effects of diversification are attributed more to returns to scale in production rather than to complementarities between different products. In contrast, the convexity effect is found to hurt economies of diversification, suggesting a possible concave property of the bank cost function. This implies that the marginal cost tends to decrease in Japan. Finally, there is also an upward trend in economies of diversification, complementarity effect, and scale effect, which is similar to the results for economies of scope and highlights the role of technological change in the cost-saving benefits of diversification.

As mentioned above, within-sample economies of scope can be considered a special case of economies of diversification. Hence, it can be decomposed in the same way. Table 3-5 reports the decomposition effects of within-sample scope economies for the whole sample and four groups divided by bank size. The sign of each effect remains unchanged, except for the negative complementarity effect in the early 2000s. This implies that positive complementarity and scale effects are still the main factors contributing to economies of scope. Table 3-5 reveals an additional insight that the magnitudes of the scale and complementarity effects may differ across the four groups, potentially explaining why small-sized banks exhibit higher within-sample scope economies. On the one hand, small-sized banks tend to have a greater scale effect, with Group 1 having an average scale effect of 0.855, which is 0.145 higher than Group 4's

average scale effect of 0.710. Since the scale effect captures the increasing returns to scale property in production, large banks find it more challenging to reduce costs by expanding their scale. This is consistent with the common pattern of return to scale, where firms tend to experience increasing returns to scale before reaching the optimum size. Subsequently, it transitions into constant and decreasing returns to scale if they are at or surpass the optimal size. On the other hand, larger banks exhibit a higher complementarity effect. This is because larger banks typically have higher business volumes and are more motivated to improve management or adopt new technologies to achieve synergies between different businesses. However, this positive effect is offset by a negative convexity effect. Overall, small-sized banks tend to rely more on the scale effect, while the complementarity effect is more significant for larger banks. The average complementarity effect for the smallest banks, Group 1, is 0.019, while the scale effect is much larger at 0.855. In contrast, the relative magnitude in other groups is not the case. For example, banks in Group 4 exhibit a higher average complementarity effect at 0.333, which is 47% of the scale effect (0.710). Notably, the result reveals a significant rise in Group 4's complementarity effect in recent years, nearing parity with the scale effect.

To sum up, the analysis shows that both the average of within-sample scope economies and economies of diversification under different specialization patterns are positive, suggesting that banks in Japan can enjoy the cost-saving benefits through diversification. Moreover, through a decomposition method proposed by Chavas and Kim (2010), we find that diversification benefits can be attributed to positive complementarity and scale effects. Meanwhile, these two effects may vary with specialization patterns and bank size.

3.4.3 Diversification and economies of scope

From the above analysis, we have estimated within-sample scope economies and economies of diversification for each bank in each year. However, this only provides industry-level evidence to show the existence of scope economies in Japan. We aim to gather additional bank-level evidence regarding diversification benefits, given that previous literature has highlighted economies of scope as a key factor contributing to such benefits. Consequently, this section attempts to figure out whether bank diversification affects the degree of economies of scope.

In order to investigate the relationship between bank diversification and scope economies, we regress estimated scope economies on the diversification variables and other control variables with a fixed effects model. According to Laeven and Levine (2007), bank diversification can be represented by asset- and income-based variables that measure the degree to which banks

specialize in lending or non-lending services. For asset diversification, we use the ratio of loans (Y_1) to total outputs (Y_1+Y_2+Y_3) as a measure of asset diversification, where a lower ratio indicates more diversification in non-traditional businesses. This is reasonable because we do not introduce new variables that are not used in the cost function, which can avoid unknown biases. In addition, a Herfindahl-Hirschman Index (HHI) that measures the concentration of the three outputs is also used as an independent variable. The asset HHI is calculated as:

$$asset\ HHI = 1 - \left[\left(\frac{Y_1}{Y_1 + Y_2 + Y_3}\right)^2 + \left(\frac{Y_2}{Y_1 + Y_2 + Y_3}\right)^2 + \left(\frac{Y_3}{Y_1 + Y_2 + Y_3}\right)^2\right] \quad (10)$$

A higher value in asset HHI implies the bank's output is more evenly distributed, reflecting a higher level of diversification. On the other hand, we also use the ratio of interest on loans and discounts to ordinary income (interest ratio) to measure income diversification. Banks with higher loan interest income ratios are considered to be more engaged in traditional business and, therefore, less diversified. Similarly, the income HHI is defined by the concentration between loan interest and other income.

The dependent variables are estimated within-sample scope economies, economies of diversification, and the complementarity effect. We also introduce several control variables: the logarithm of bank assets (assets), to control for bank size; the ratio of non-performing loans (npl), to control for risk; the variables in the cost function, such as input price, and equity capital. Finally, standard errors are clustered at the bank level.

Panel A and panel B of Table 3-6 report the regression results for the effect of asset and income diversification on scope economies, respectively. Columns (1) to (4) show the results for the total effects, while Columns (5) to (8) focus on the complementarity effect. For economies of diversification, considering the space limitations, we only report the results when β is equal to 0.8. The signs of the coefficients remain unchanged for the other specialization patterns (β=0.9 or 0.7).

We find a significant negative relationship between diversification and scope economies from the regressions. In panel A, the ratio of loan to total outputs (loan ratio) is positively linked with within-sample economies of scope and economies of diversification, which are both significant at the 1% level. It means scope economies are higher when the banks engage more in the traditional loan-making business. Another diversification measure, asset HHI, is found to have a significant negative impact on scope economies, suggesting that an equal distribution across the three outputs leads to a decrease in scope economies. The estimates of the decline

in scope economies due to a more diversified output portfolio are −1.046 for within-sample scope economies and −0.355 for economies of diversification. Furthermore, the conclusions still hold when focusing on complementary effects since the signs and significance levels of the corresponding coefficients remain unchanged. We also find that the slopes of linear regression models in columns (5) to (8) are slightly sharper, which may indicate a more pronounced negative effect of diversification on the complementarity effect. As for the income diversification in panel B, the coefficients of interest income ratio are significantly positive in all regressions, which confirms the above results for asset diversification. However, we do not find similar results for the income HHI, which has a negative but not significant coefficient. The regression results are consistent with what we find in Table 3-4, that is, the complementarity effect decreases with the decrease of specialization pattern (β). Table 3-4 depicts a situation where for the same bank, the cost-saving benefits from complementarity effects are more minor compared to less specialized banks than compared to highly specialized banks. Conversely, the results in this section show that the complementarity effect is smaller for banks with higher levels of diversification, even at a fixed β. In a word, these two results tell the same story from different perspectives, namely that being more diversified may not achieve a higher degree of scope economies.

The negative relationship can be attributed to the growing complexity associated with producing more non-lending outputs. As traditional banks extend into non-lending businesses, the cost-saving effect is substantial, as fewer inputs are needed to generate a small number of other outputs. However, as banks diversify further, the non-lending businesses become more complex, requiring additional diverse inputs to produce greater outputs, thereby diminishing the cost-saving effect.

As for the control variables in regressions, the coefficients of equity capital are significantly negative at the 1% level, implying that banks with higher equity capital may have smaller scope economies. This result can be explained by the findings of Hughes and Mester (1998) that bank managers are risk averse and tend to increase financial capital to control risk and employ additional inputs to improve risk management. Thus, for given a vector of outputs, banks with higher equity capital may invest more in controlling risk than in production, thereby diluting the scope economies. In addition, bank size is positively correlated with scope economies, indicating larger banks have an advantage in scope economies. This does not conflict with what we find in Table 3-3 because other variables are not held constant in calculating group differences.

However, this approach may suffer from endogeneity problems because the regression model

is set up in a simple linear way. To deal with this problem, we first add the quadratic terms of key independent variables in the model to check whether there is a nonlinear relationship. The results show that the coefficients of quadratic terms are not statistically significant (the results are not shown), implying no nonlinear relations. Second, we run the 2SLS model using the first-order lags of the diversification variables as instrumental variables. The IV regression results are presented in Appendix 2, and the negative relationship remains robust.

In summary, the analysis in this section provides strong evidence that scope economies exist in the Japanese banking industry. The cost-saving effects from joint production encourage banks to expand their business scope and thus become more diversified. This may explain why diversification benefits are often found in studies on Japanese banks. Moreover, with the increase in diversification, scope economies are found to decline. In other words, even though banks still have positive scope economies, diversified banks seem to benefit less from scope economies. This may be one reason why banks are not eager to seek a higher level of diversification.

3.5. Robustness

3.5.1 Conventional estimates of economies of scope

As noted in section 4, we try to measure scope economies for every bank using its original data. However, prior literature usually estimates it from the industry level, with all variables at their sample means. This is thought to be more accurate since the translog function is second-order Taylor expansion at the sample mean. Therefore, we also follow this method to calculate scope economies at the sample means. Table 3-7 reports the results for within-sample scope economies (first row in each group) and economies of diversification (second row, β=0.8) when outputs take the mean value of the whole sample or each group divided by bank assets and other variables take their sample means[20]. In addition, We use the Wald test to measure the significant level of the estimations.

The results show that the economies scope remains positive when estimated at the mean values, indicating similar results as above. More importantly, the validity of the estimates is confirmed by the Wald test, as all estimates are statistically significant, except for the within-sample scope economies in Group 4. We also find that small-sized banks with larger within-scope economies are only present between Groups 1 to 3 until 2010, whereas within-sample

[20] The bank heterogeneity (α_i) captures the individual effect, and we the mean value of α_i to esitimate the scope economies of a representative bank.

scope economies are considerably larger in Group 4. This result is partly consistent with the results presented in Table 3-3.

3.5.2 Estimates without city banks

Commercial banks in Japan are generally categorized into four types: city banks, regional banks, second regional banks, and others. Compared with city banks, other banks are much smaller in size and restricted to operating in a limited area. Thus, the previously estimated cost function may be biased when city banks are included since the translog cost function is less reliable if banks are widely varying in size (Wheelock and Wilson, 2012). In order to exclude the influence from larger banks, we re-estimate the cost function for the sample without city banks[21].

Table 3-8 presents the mean value of scope economies and their decomposition effects[22] for the remaining banks, which are consistent with the outcomes shown in Table 3-4 and Table 3-5. The positive average scope economies support that, on average, banks can enjoy economies of scope even if the cost function is estimated without city banks. However, the within-sample scope economies are found to be greater than the results in Table 3-5, due to a larger estimated complementarity effect from the new cost function. In contrast, there are no significant changes in economies of diversification compared with Table 3-4. One possible explanation is that the new cost function is more sensitive to the specialization pattern in securities and OBS outputs as most banks display lower specialization in these two businesses. As for the other two decomposition effects, the scale and convexity effects retain their respective signs.

Table 3-9 reports the results of scope economies regressed by bank diversification. The signs of asset and income diversification variables remain unchanged. This indicates that the negative relationship between scope economies and diversification still holds after excluding the influence of large-sized banks.

3.5.3 Net non-interest income as a measure of off-balance sheet activities

Although we choose the nominal values of some non-traditional operation items as a proxy of banks' OBS activities, it still suffers from the problem of underestimating the true value. Therefore, we use the net non-interest income as an alternative measure for OBS and redo our

[21] Two transformed Long-Term Credit Banks are not excluded here because their assets are not larger than those of other regional banks.

[22] We choose β=0.8 as a representative example to estimate economies of diversification. Other specialization patterns are also calculated but are not shown due to space limitations.

analysis as many previous studies have done. The net non-interest income is measured as the net income from fees and commissions and trading[23], which is the non-interest part of the banks' gross profit from core businesses. Other income in a Japanese bank's income statement is not included because the net income of this item is highly negative, making it an undesirable measure for net income.

Table 3-10 reports the mean value of scope economies using net non-interest income to measure banks' OBS activities. Evidence that supports the existence of scope economies is also found even when a "flow" variable is used in the cost function. The decomposition effects demonstrate a similar trend as observed in the previous analysis. Furthermore, the results for within-sample scope economies are, on average, larger than those in Table 3-5. In particular, the complementarity effect constitutes a significant share of the total effect, suggesting a strong complementarity relationship with the new OBS measures.

The regression results in Table 3-11 also indicate that the relationship between scope economies and the diversification level remains unchanged when net non-interest income is treated as a proxy of OBS activities. However, regressions (3) and (4) tell a different story, where diversified banks have higher economies of diversification with β=0.8. We further set other specialization patterns and find the results vary with β. For example, the coefficient of loan ratio becomes positive when β is 0.9 while it remains negative when β is 0.7. These results indicate that using a "flow" variable may introduce unknown biases in the estimation and researchers should pay attention to the mixing variables problem.

3.5.4 Fourier flexible function

While the translog function has been one of the most popular forms of cost functions since researchers began to focus on productivity issues, the use of the translog function to estimate costs has recently been controversial. The main drawback of the translog function is that it is derived from a Taylor expansion of the cost function around the sample mean. Thus, the estimated cost may be biased if the bank size varies widely (see more in Wheelock and Wilson, 2001, Wheelock and Wilson, 2012, Mitchell and Onvural, 1996). In contrast, the Fourier series can exactly represent an arbitrary function due to the mutual orthogonal and function space-spanning of the cosine and sine functions. Although an infinite number of trigonometric terms are theoretically required to represent an unknown function fully, Gallant (1981) shows that including a second-order polynomial can effectively reduce the approximation error when only

[23] In a Japanese bank's income statement, the income from trading includes the gain on the trading account transactions and other ordinary income.

fewer trigonometric terms are introduced. As shown below, the FF function consists of a standard translog function and truncated Fourier series, making it closer to the true cost function within finite parameters. Moreover, even if we do not impose any concavity or monotonicity restrictions on the parameters of the Fourier series part, it will not affect the approximation results for the true cost function (Gallant, 1982).

Following Berger and Mester (2003), the Fourier Flexible function is set as follows:

$$\begin{aligned}\ln\frac{C}{p_3} = {} & \alpha_i + \sum_{m=1}^{3}\alpha_m \ln y_{m,it} + \sum_{k=1}^{2}\beta_k \ln\frac{p_{k,it}}{p_3} + \gamma_0 \ln E_{it} + \delta_0 T + \sum_{m=1}^{3}\sum_{n=1}^{3}\alpha_{mn} \ln y_{m,it} \ln y_{n,it} \\ & + \sum_{k=1}^{2}\sum_{l=1}^{2}\beta_{kl} \ln\frac{p_{k,it}}{p_3}\ln\frac{p_{l,it}}{p_3} + \gamma_{00} \ln E_{it}^2 + \delta_{00} T^2 + \sum_{m=1}^{3}\sum_{k=1}^{2}\gamma_{mk} \ln y_{m,it} \ln\frac{p_{l,it}}{p_3} \\ & + \sum_{m=1}^{3}\gamma_m \ln y_{m,it} \ln E_{it} + \sum_{m=1}^{3}\delta_m \ln y_{m,it}\, T + \sum_{k=1}^{2}\theta_k \ln\frac{p_{k,it}}{p_3}\ln E_{it} \\ & + \sum_{k=1}^{2}\mu_k \ln\frac{p_{k,it}}{p_3} T + \varphi_0 \ln E_{it}\, T + \sum_{m=1}^{3}[\theta_m \cos q_m + \varphi_m \sin q_m] \\ & + \sum_{m=1}^{3}\sum_{n=1}^{3}[\theta_{mn} \cos(q_m + q_n) + \varphi_{mn} \sin(q_m + q_n)] + u_{it} + u_{it} + v_{it}\end{aligned} \tag{11}$$

where q_m and q_n are the rescaled value of ln(y), restricted to the interval $[0.2\pi,1.8\pi]$. q_m is calculated as $0.2\pi - \mu_k \times a_k + \mu_k \times ln(Y_m)$, where $\mu_k \equiv (0.9 \times 2\pi - 0.1 \times 2\pi)/(b_k - a_k)$ and $a_k = ln(Y_k^{min})$, $b_k = ln(Y_k^{max})$. It is also important to note that only the trigonometric terms of outputs are included in the cost function, which is different from a complete FF cost function discussed in Feng and Serletis (2009). This is a compromise since fewer parameters need to be estimated within a limited sample, but the results may be somewhat biased.

Table 3-12 summarizes the within-sample scope economies and decomposition effects estimated using the Fourier flexible function. The outcomes reveal a more pronounced presence of economies of scope when compared to Table 3-2 as all banks present positive scope economies. This supports that economies of scope still exist when a more flexible cost function is employed. However, However, caution is warranted, as the estimation may be biased due to the unreliability of the maximum value. Notably, our analysis suggests that larger banks tend to be over-estimated in terms of scope economies, indicating that the reduced form of FF function performs poorly for larger values. On the other hand, the results of decomposition effects also validate the positive impact of complementarity and scale effect on the total effect. Additionally, the complementarity effect is found to dominate over other effects after 2007.

Table 3-13 reports the regression results for scope economies, estimated by a Fourier flexible cost function. The dependent variable in columns (1) to (4) is within-sample scope economies and the complementarity effect in columns (5) to (8). Similarly, scope economies estimated from two different cost functions are both found to be negatively linked with bank diversification. The above analysis indicates that even though the translog function is not as accurate as many researchers would expect, it is still useful in practice since the results are similar.

3.6. Conclusion

The debate over whether banks benefit from diversification remains controversial due to the challenge of theorizing the factors contributing to diversification benefits or discounts, with few studies offering concrete empirical evidence. While many researchers consider economies of scope as the main factor contributing to diversification benefits, studies related to scope economies are somewhat outdated in data and estimation methodology. Motivated by Beccalli and Rossi (2020) and Zhang and Malikov (2022), who recently found significant positive scope economies in the EU and U.S. banking sectors, this paper re-estimates scope economies for 120 Japanese commercial banks from 2000 to 2020. Using a translog cost function, we estimate the bank cost frontier by the stochastic frontier analysis (SFA) approach. In addition to the widely used indicator, within-sample scope economies, we employ a new measure proposed by Chavas and Kim (2010) called economies of diversification, which measures the cost-saving effects under partial specialization. This measure provides a framework to decompose the economies of diversification into four parts: complementarity, scale, convexity, and fixed cost effects, enabling a thorough analysis of the contributing factors. Furthermore, we also explore the effect of bank diversification on the magnitude of scope economies through regression analysis.

The results show significantly positive scope economies in the Japanese banking industry. For within-sample economies of scope, it is found that, on average, the cost for specialized production is 0.549 times higher than that of joint production and 99% of Japanese banks exhibit positive economies of scope. Compared with other banks, small-sized banks have a relatively larger degree of scope economies. This may be explained by the decomposition of within-sample economies of scope, that is, small-sized banks have a relatively higher scale effect. The results also show that average scope economies have been increasing over the 21 years, implying a vital role of technology improvement in cost-saving. On the other hand,

economies of diversification are also found to be positive under different specialization patterns, indicating that diversified banks can save costs even under partial specialization. The decomposed effects results suggest that economies of diversification are driven by positive complementarity and scale effects. Moreover, the regression results show that estimated scope economies are negatively correlated with diversification, suggesting that being more diversified may not bring higher scope economies.

This study provides new evidence to explain the observed benefits of bank diversification in Japan. Diversified banks can achieve higher profits or be more valued by the market since they can save costs through joint production. However, our findings also suggest that the magnitude of scope economies decreases when banks become more diversified. This implies that not all banks should seek a relatively high diversification level. Finally, it is important to note that economies of scope are one aspect of diversification effects. The net effects may turn negative if other adverse factors, such as agency problems, outweigh the benefits. Therefore, further research is necessary to understand the effects of bank diversification comprehensively.

Tables

Table 3-1 Summary statistic

Variable	Obs.	Mean	Std. dev	Min	Max
C	2083	79816	255434	3580	2925984
Y_1	2083	4046514	11515557	164788	104109320
Y_2	2083	1824099	6187841	26572	65884960
Y_3	2083	2579843	11366470	1633	115952280
Equity	2083	360894	1168362	4876	12147420
P_1	2083	0.001	0.001	0.000	0.019
P_2	2083	6.099	0.907	3.580	9.425
P_3	2083	0.557	0.241	0.122	2.388
T	2083	10.506	5.870	1	21

Note: C – total cost; Y_1 – loans; Y_2 – securities; Y_3 – off-balance sheet activities; Equity – equity capital; P_1 – price of deposits; P_2 – price of labor; P_3 – price of physical capital; T – time variable. Variables C, Y_1, Y_2, Y_3, Equity, and P_2 are in millions of yen.

Table 3-2 Results of within-sample scope economies over time

Year	Obs.	Mean	Min	Max	>0	Goup1	Group2	Group3	Group4
2000	77	0.276	-0.126	0.715	94.81%	0.465	0.279	0.117	0.019
2001	77	0.343	-0.028	0.831	98.70%	0.533	0.364	0.164	0.124
2002	79	0.409	0.048	0.912	100%	0.581	0.425	0.240	0.245
2003	85	0.428	0.005	0.920	100%	0.612	0.433	0.266	0.231
2004	89	0.431	-0.201	0.957	97.75%	0.629	0.447	0.291	0.198
2005	91	0.425	-0.202	0.925	97.80%	0.632	0.452	0.318	0.187
2006	92	0.390	-0.131	1.112	96.74%	0.626	0.417	0.285	0.151
2007	92	0.413	-0.109	1.417	97.83%	0.658	0.421	0.307	0.204
2008	92	0.505	0.041	0.963	100%	0.691	0.503	0.399	0.366
2009	91	0.476	0.062	0.799	100%	0.651	0.501	0.388	0.332
2010	89	0.517	-0.005	0.875	98.88%	0.697	0.565	0.450	0.380
2011	90	0.549	0.059	0.929	100%	0.733	0.591	0.498	0.408
2012	88	0.563	0.106	0.833	100%	0.740	0.613	0.503	0.456
2013	87	0.608	0.160	0.900	100%	0.764	0.666	0.532	0.536
2014	84	0.609	0.218	0.889	100%	0.759	0.673	0.531	0.548
2015	79	0.651	0.257	0.972	100%	0.786	0.701	0.594	0.605
2016	78	0.716	0.314	1.121	100%	0.834	0.755	0.667	0.674
2017	79	0.761	0.315	1.099	100%	0.874	0.802	0.723	0.710
2018	71	0.810	0.348	1.189	100%	0.909	0.842	0.785	0.756
2019	70	0.891	0.393	1.277	100%	0.960	0.902	0.865	0.862
2020	69	0.963	0.471	1.476	100%	1.005	0.966	0.917	0.967
Total	1749	0.549	-0.202	1.476	99.14%	0.690	0.544	0.476	0.485

Note: This table presents the results for estimated within-sample scope economies, including the mean, minimum, and maximum values for each year. Colum 6 (“>0”) shows the proportion of positive estimations. Groups 1 to 4 (small to large) are divided by bank assets in each year, and the mean value of within-sample scope economies within each group is reported.

Table 3-3 The difference in scope economies among four groups

	Group2	Group3	Goup4
Group1	**0.146**	**0.215**	**0.206**
Group2		**0.068**	**0.059**
Group3			-0.009

Note: This table presents the results of the t-test on estimated within-sample scope economies across different groups. Groups 1 to 4 (small to large) are divided by bank assets in each year. The bold typeface indicates the difference between the two groups is significantly different from 0 at the 5% level.

Table 3-4 Results of economies of diversification with different β

Year	β =0.9				β =0.8				β =0.7			
	Div	S_C	S_R	S_V	Div	S_C	S_R	S_V	Div	S_C	S_R	S_V
2000	0.451	0.110	0.697	-0.357	0.529	0.052	0.697	-0.220	0.594	0.027	0.697	-0.130
2001	0.517	0.146	0.741	-0.370	0.586	0.072	0.741	-0.227	0.646	0.038	0.741	-0.134
2002	0.568	0.171	0.778	-0.381	0.630	0.086	0.778	-0.233	0.687	0.046	0.778	-0.137
2003	0.577	0.174	0.786	-0.382	0.640	0.087	0.786	-0.234	0.696	0.047	0.786	-0.138
2004	0.584	0.174	0.794	-0.384	0.647	0.088	0.794	-0.235	0.704	0.047	0.794	-0.138
2005	0.574	0.168	0.788	-0.382	0.639	0.085	0.788	-0.233	0.696	0.046	0.788	-0.137
2006	0.543	0.158	0.760	-0.375	0.609	0.078	0.760	-0.229	0.667	0.042	0.760	-0.135
2007	0.558	0.176	0.755	-0.373	0.613	0.087	0.755	-0.229	0.667	0.047	0.755	-0.135
2008	0.610	0.214	0.776	-0.379	0.650	0.106	0.776	-0.232	0.696	0.057	0.776	-0.137
2009	0.588	0.195	0.771	-0.379	0.637	0.097	0.771	-0.232	0.687	0.052	0.771	-0.137
2010	0.624	0.212	0.798	-0.385	0.669	0.106	0.798	-0.235	0.717	0.057	0.798	-0.138
2011	0.641	0.219	0.810	-0.389	0.684	0.110	0.810	-0.237	0.731	0.060	0.810	-0.139
2012	0.647	0.222	0.814	-0.390	0.689	0.112	0.814	-0.237	0.735	0.061	0.814	-0.139
2013	0.682	0.243	0.833	-0.394	0.717	0.123	0.833	-0.240	0.759	0.067	0.833	-0.141
2014	0.685	0.245	0.835	-0.394	0.719	0.124	0.835	-0.240	0.761	0.067	0.835	-0.141
2015	0.719	0.267	0.850	-0.398	0.744	0.135	0.850	-0.241	0.782	0.073	0.850	-0.142
2016	0.772	0.300	0.875	-0.403	0.783	0.152	0.875	-0.244	0.815	0.082	0.875	-0.143
2017	0.815	0.330	0.891	-0.405	0.813	0.167	0.891	-0.245	0.838	0.090	0.891	-0.143
2018	0.858	0.359	0.906	-0.407	0.841	0.181	0.906	-0.245	0.860	0.098	0.906	-0.143
2019	0.923	0.399	0.935	-0.412	0.888	0.201	0.935	-0.247	0.899	0.108	0.935	-0.144
2020	0.963	0.413	0.966	-0.416	0.924	0.208	0.966	-0.250	0.933	0.113	0.966	-0.146
Total	0.650	0.225	0.811	-0.387	0.689	0.113	0.811	-0.236	0.734	0.061	0.811	-0.139

Note: This table presents the results for estimated economies of diversification under three different levels of diversification assumption, measured by β. A larger β means that the bank is more specialized in one output, and thus less diversified. For each β, the mean value of economies of diversification, and three decomposed effects are reported.

Table 3-5 Decomposition effects of within-sample scope economies

Year	Whole sample			Group 1			Gourp 2			Group 3			Group 4		
	S_C	S_R	S_V	S_C	S_R	S_V	S_C	S_R	S_V	S_C	S_R	S_V	S_C	S_R	S_V
2000	-0.048	0.670	-0.346	-0.023	0.709	-0.221	-0.044	0.696	-0.373	-0.086	0.642	-0.439	-0.061	0.542	-0.462
2001	-0.013	0.714	-0.358	-0.008	0.758	-0.216	-0.001	0.741	-0.376	-0.060	0.681	-0.457	0.017	0.602	-0.495
2002	0.025	0.751	-0.367	-0.001	0.788	-0.205	0.025	0.783	-0.383	-0.014	0.729	-0.475	0.134	0.639	-0.528
2003	0.029	0.765	-0.367	0.002	0.815	-0.205	0.030	0.794	-0.391	-0.001	0.742	-0.474	0.122	0.637	-0.527
2004	0.027	0.774	-0.371	-0.001	0.827	-0.197	0.034	0.809	-0.396	0.014	0.755	-0.479	0.081	0.650	-0.533
2005	0.032	0.767	-0.374	0.004	0.826	-0.198	0.035	0.805	-0.388	0.030	0.764	-0.476	0.073	0.636	-0.521
2006	0.024	0.742	-0.376	0.009	0.817	-0.200	0.022	0.776	-0.381	0.025	0.729	-0.469	0.046	0.613	-0.509
2007	0.049	0.736	-0.372	0.022	0.824	-0.188	0.032	0.756	-0.367	0.052	0.720	-0.465	0.101	0.616	-0.514
2008	0.115	0.757	-0.367	0.037	0.832	-0.178	0.080	0.782	-0.359	0.124	0.739	-0.464	0.252	0.643	-0.530
2009	0.103	0.755	-0.381	0.016	0.818	-0.184	0.079	0.787	-0.365	0.123	0.735	-0.470	0.217	0.654	-0.539
2010	0.137	0.777	-0.397	0.028	0.848	-0.180	0.105	0.815	-0.355	0.155	0.765	-0.470	0.249	0.684	-0.553
2011	0.158	0.795	-0.404	0.020	0.880	-0.167	0.124	0.828	-0.361	0.187	0.793	-0.482	0.275	0.691	-0.557
2012	0.180	0.800	-0.417	0.019	0.888	-0.168	0.142	0.835	-0.364	0.193	0.796	-0.486	0.317	0.706	-0.567
2013	0.213	0.819	-0.424	0.033	0.906	-0.175	0.175	0.856	-0.365	0.205	0.813	-0.485	0.371	0.737	-0.571
2014	0.218	0.819	-0.428	0.032	0.909	-0.182	0.179	0.870	-0.376	0.192	0.809	-0.471	0.379	0.739	-0.570
2015	0.259	0.833	-0.441	0.041	0.923	-0.178	0.198	0.874	-0.372	0.227	0.842	-0.476	0.431	0.755	-0.580
2016	0.298	0.859	-0.441	0.049	0.951	-0.167	0.231	0.904	-0.379	0.265	0.875	-0.473	0.484	0.774	-0.584
2017	0.325	0.876	-0.44	0.056	0.976	-0.157	0.262	0.921	-0.381	0.301	0.900	-0.478	0.519	0.779	-0.587
2018	0.354	0.887	-0.431	0.060	0.994	-0.145	0.288	0.933	-0.379	0.341	0.923	-0.479	0.570	0.776	-0.591
2019	0.405	0.916	-0.430	0.066	1.027	-0.134	0.323	0.957	-0.379	0.392	0.953	-0.480	0.663	0.801	-0.602
2020	0.448	0.949	-0.433	0.060	1.059	-0.115	0.340	0.987	-0.361	0.398	0.991	-0.471	0.722	0.852	-0.608
Mean	0.151	0.795	-0.397	0.019	0.855	-0.184	0.101	0.817	-0.374	0.153	0.796	-0.473	0.333	0.710	-0.558

Note: This table presents the decomposed effects of within-sample scope economies under the framework of Chavas and Kim (2010). The mean values of decomposed effects are reported for the whole sample and groups of banks of different sizes. Groups 1 to 4 (small to large) are divided by bank assets in each year,

Table 3-6 Regression results for the relationship between diversification and scope economies

Panel A: asset diversification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Within-sample scope economies		Economies of diversification (β=0.8)		Complementarity effect for within-sample		Complementarity effect (β=0.8)	
loan ratio	0.930***		0.321***		1.067***		0.397***	
	(0.108)		(0.029)		(0.134)		(0.018)	
asset HHI		-0.952***		-0.347***		-1.099***		-0.463***
		(0.148)		(0.041)		(0.178)		(0.027)
ln E	-0.298***	-0.303***	-0.188***	-0.191***	-0.126***	-0.133***	-0.057***	-0.061***
	(0.021)	(0.022)	(0.008)	(0.008)	(0.020)	(0.020)	(0.005)	(0.004)
$\ln\frac{p_1}{p_3}$	-0.059***	-0.058***	-0.051***	-0.051***	-0.021	-0.020	-0.012***	-0.010***
	(0.018)	(0.018)	(0.003)	(0.003)	(0.017)	(0.017)	(0.002)	(0.002)
$\ln\frac{p_2}{p_3}$	0.011	0.011	0.093***	0.092***	-0.032	-0.033	0.017***	0.016***
	(0.022)	(0.023)	(0.004)	(0.005)	(0.024)	(0.025)	(0.003)	(0.003)
assets	0.344***	0.334***	0.033***	0.030**	0.419***	0.408***	0.008	0.004
	(0.058)	(0.061)	(0.012)	(0.012)	(0.063)	(0.066)	(0.007)	(0.007)
npl	0.176	0.063	0.049	0.010	0.212	0.082	0.050	-0.008
	(0.179)	(0.204)	(0.071)	(0.066)	(0.166)	(0.189)	(0.062)	(0.055)
cons	-2.241***	-0.937	1.475***	1.936***	-5.483***	-3.979***	0.212**	0.823***
	(0.826)	(0.913)	(0.172)	(0.178)	(0.882)	(0.981)	(0.085)	(0.097)
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	1749	1749	2083	2083	1749	1749	2083	2083
R^2(within)	0.912	0.905	0.981	0.980	0.852	0.840	0.956	0.958

Panel B: income diversification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Within-sample scope economies		Economies of diversification (β=0.8)		Complementarity effect for within-sample		Complementarity effect (β=0.8)	
interest ratio	0.235**		0.114***		0.290***		0.121***	
	(0.102)		(0.027)		(0.106)		(0.024)	
income HHI		-0.122		0.022		-0.110		-0.046
		(0.173)		(0.055)		(0.195)		(0.050)
ln E	-0.291***	-0.289***	-0.187***	-0.185***	-0.118***	-0.116***	-0.055***	-0.054***
	(0.020)	(0.021)	(0.007)	(0.008)	(0.022)	(0.022)	(0.005)	(0.005)
$\ln\frac{p_1}{p_3}$	-0.064***	-0.061***	-0.053***	-0.052***	-0.027	-0.023	-0.014***	-0.012***
	(0.017)	(0.018)	(0.003)	(0.003)	(0.017)	(0.018)	(0.002)	(0.002)
$\ln\frac{p_2}{p_3}$	0.026	0.023	0.100***	0.100***	-0.015	-0.019	0.026***	0.026***
	(0.024)	(0.026)	(0.005)	(0.006)	(0.027)	(0.030)	(0.005)	(0.006)
assets	0.357***	0.362***	0.038***	0.041***	0.433***	0.440***	0.015	0.016
	(0.062)	(0.065)	(0.013)	(0.014)	(0.069)	(0.072)	(0.011)	(0.012)
npl	0.256	0.301	0.093	0.116*	0.299	0.357	0.109**	0.131**
	(0.252)	(0.229)	(0.058)	(0.068)	(0.247)	(0.219)	(0.053)	(0.061)
cons	-2.128**	-2.015**	1.502***	1.489***	-5.355***	-5.246***	0.247*	0.308*
	(0.904)	(0.958)	(0.189)	(0.206)	(0.996)	(1.050)	(0.144)	(0.164)
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	1749	1749	2083	2083	1749	1749	2083	2083
R^2(within)	0.891	0.889	0.974	0.972	0.816	0.810	0.895	0.884

Note: This table examines the relationship between estimated scope economies measures and bank diversification. Panels A and B present results for asset and income diversification, respectively. Specifications include bank and year fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table 3-7 Robustness: results for conventional estimates of scope economies

	2000	2005	2010	2015	2020
Sample mean	0.326*	0.510*	0.714**	1.167**	1.651**
	0.572***	0.682***	0.769***	0.902***	1.019***
Group 1	0.411***	0.446***	0.503***	0.558***	0.644***
	0.440***	0.512***	0.585***	0.662***	0.778***
Group 2	0.312***	0.391***	0.507***	0.638***	0.740***
	0.503***	0.572***	0.656***	0.745***	0.854***
Group 3	0.314**	0.415***	0.583***	0.738***	0.880***
	0.546***	0.615***	0.706***	0.789***	0.884***
Group 4	0.893	1.278	1.544	2.256	3.042*
	0.700***	0.795***	0.870***	0.993***	1.103***

Note: This table presents the results for an alternative conventional measure of economies of scope. Groups 1 to 4 (small to large) are divided by bank assets in each year. The first row in each group reports within-sample scope economies, and the second row reports economies of diversification under β=0.8. The significant level is measured by the Wald test. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table 3-8 Robustness: results without city banks

Year	Within-sample scope economies					Economies of diversification, β =0.8				
	N	Div	S_C	S_R	S_V	N	Div	S_C	S_R	S_V
2000	74	0.596	0.359	0.546	-0.309	98	0.425	0.115	0.535	-0.226
2001	74	0.684	0.411	0.610	-0.337	99	0.489	0.136	0.596	-0.243
2002	75	0.753	0.444	0.669	-0.359	99	0.550	0.155	0.653	-0.258
2003	80	0.770	0.442	0.691	-0.363	102	0.572	0.163	0.672	-0.263
2004	84	0.805	0.471	0.705	-0.371	104	0.590	0.168	0.689	-0.267
2005	86	0.836	0.511	0.701	-0.376	103	0.595	0.172	0.690	-0.267
2006	87	0.854	0.561	0.656	-0.363	104	0.558	0.170	0.643	-0.255
2007	87	0.921	0.636	0.638	-0.353	104	0.562	0.186	0.626	-0.251
2008	87	1.028	0.720	0.670	-0.362	104	0.608	0.209	0.658	-0.259
2009	86	1.040	0.739	0.681	-0.381	102	0.607	0.202	0.666	-0.262
2010	84	1.144	0.831	0.722	-0.409	100	0.657	0.219	0.711	-0.272
2011	85	1.218	0.890	0.753	-0.425	100	0.686	0.229	0.735	-0.278
2012	83	1.315	0.992	0.767	-0.444	97	0.706	0.238	0.749	-0.281
2013	83	1.406	1.072	0.792	-0.457	97	0.741	0.253	0.773	-0.286
2014	80	1.429	1.096	0.794	-0.461	94	0.745	0.256	0.775	-0.286
2015	75	1.556	1.220	0.811	-0.475	88	0.780	0.275	0.795	-0.291
2016	74	1.630	1.266	0.848	-0.484	86	0.831	0.296	0.833	-0.298
2017	75	1.728	1.345	0.871	-0.488	86	0.872	0.318	0.856	-0.302
2018	67	1.842	1.440	0.878	-0.477	76	0.905	0.338	0.871	-0.305
2019	66	1.961	1.528	0.918	-0.485	75	0.962	0.365	0.909	-0.311
2020	65	2.019	1.551	0.968	-0.500	73	1.016	0.375	0.959	-0.318
Total	1657	1.193	0.862	0.742	-0.411	1991	0.674	0.224	0.723	-0.273

Note: This table presents the mean value of within-sample scope economies and economies of diversification, and their decomposed effects when city banks are excluded from the sample.

Table 3-9 Robustness: regression results without city banks

Panel A: asset diversification								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Within-sample scope economies		Economies of diversification (β=0.8)		Complementarity effect for within-sample		Complementarity effect (β=0.8)	
loan ratio	2.973***		0.447***		3.202***		0.581***	
	(0.609)		(0.035)		(0.629)		(0.026)	
assset HHI		-2.828***		-0.462***		-3.093***		-0.655***
		(0.791)		(0.046)		(0.815)		(0.033)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	1657	1657	1991	1991	1657	1657	1991	1991
R^2	0.773	0.762	0.989	0.988	0.740	0.728	0.975	0.976
Panel B: income diversification								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Within-sample scope economies		Economies of diversification (β=0.8)		Complementarity effect for within-sample		Complementarity effect (β=0.8)	
interest ratio	0.693*		0.138***		0.764*		0.169***	
	(0.409)		(0.030)		(0.422)		(0.030)	
income HHI		-0.240		0.002		-0.294		-0.069
		(0.689)		(0.060)		(0.723)		(0.066)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	1657	1657	1991	1991	1657	1657	1991	1991
R^2	0.746	0.743	0.982	0.981	0.706	0.703	0.927	0.919

Note: This table examines the relationship between estimated scope economies measures and bank diversification when city banks are excluded from the sample. Panels A and B present results for asset and income diversification, respectively. Controls include ln E, $\ln\frac{p_1}{p_3}$, $\ln\frac{p_2}{p_3}$, assets and npl. Specifications include bank and year fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts *, **, *** denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table 3-10 Robustness: results for a new measure of OBS activities

Year	Within-sample scope economies					Economies of diversification, β =0.8				
	N	Div	S_C	S_R	S_V	N	Div	S_C	S_R	S_V
2000	77	0.576	0.130	0.639	-0.192	99	0.527	0.063	0.683	-0.220
2001	74	0.605	0.138	0.677	-0.210	98	0.573	0.075	0.726	-0.227
2002	75	0.615	0.142	0.714	-0.241	95	0.600	0.076	0.756	-0.232
2003	81	0.609	0.128	0.726	-0.245	101	0.611	0.078	0.767	-0.234
2004	89	0.628	0.133	0.736	-0.241	107	0.617	0.079	0.772	-0.234
2005	91	0.643	0.158	0.728	-0.242	106	0.610	0.078	0.763	-0.232
2006	92	0.719	0.232	0.704	-0.217	108	0.597	0.087	0.738	-0.228
2007	83	0.832	0.334	0.702	-0.204	98	0.617	0.107	0.737	-0.227
2008	62	0.900	0.426	0.711	-0.237	71	0.645	0.124	0.750	-0.229
2009	91	0.813	0.313	0.731	-0.231	106	0.643	0.111	0.765	-0.233
2010	87	0.816	0.328	0.747	-0.259	102	0.661	0.111	0.785	-0.235
2011	90	0.839	0.335	0.769	-0.266	105	0.680	0.115	0.803	-0.238
2012	87	0.846	0.365	0.763	-0.282	101	0.675	0.113	0.798	-0.237
2013	86	0.906	0.403	0.783	-0.280	100	0.700	0.122	0.818	-0.239
2014	84	0.917	0.420	0.776	-0.278	98	0.697	0.123	0.812	-0.238
2015	77	0.996	0.497	0.781	-0.282	89	0.710	0.132	0.816	-0.239
2016	76	1.043	0.521	0.804	-0.282	87	0.740	0.144	0.837	-0.241
2017	71	1.092	0.585	0.801	-0.294	78	0.732	0.147	0.825	-0.240
2018	66	1.209	0.661	0.817	-0.270	73	0.772	0.165	0.847	-0.240
2019	66	1.284	0.712	0.845	-0.272	71	0.799	0.175	0.867	-0.243
2020	63	1.250	0.673	0.869	-0.292	67	0.812	0.169	0.888	-0.245
Total	1668	0.849	0.350	0.751	-0.252	1960	0.660	0.111	0.784	-0.234

Note: This table presents the mean value of within-sample scope economies and economies of diversification, and their decomposed effects when OBS activities are proxied by non-interest income.

Table 3-11 Robustness: regression results for a new measure of OBS activities

Panel A: asset diversification								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Within-sample scope economies		Economies of diversification (β=0.8)		Complementarity effect for within-sample		Complementarity effect (β=0.8)	
loan ratio	0.789***		-0.052**		0.945***		0.215***	
	(0.168)		(0.026)		(0.177)		(0.015)	
assset HHI		-0.654***		0.062**		-0.822***		-0.240***
		(0.199)		(0.028)		(0.215)		(0.017)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
bank fixed	YES	YES	YES	YES	YES	YES	YES	YES
time fixed	YES	YES	YES	YES	YES	YES	YES	YES
N	1668	1668	1960	1960	1668	1668	1960	1960
R^2	0.687	0.682	0.965	0.966	0.634	0.627	0.937	0.942
Panel B: income diversification								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Within-sample scope economies		Economies of diversification (β=0.8)		Complementarity effect for within-sample		Complementarity effect (β=0.8)	
interest ratio	0.840***		0.066***		0.890***		0.117***	
	(0.302)		(0.022)		(0.303)		(0.014)	
income HHI		-0.036		0.034		-0.024		-0.031
		(0.331)		(0.041)		(0.359)		(0.035)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
bank fixed	YES	YES	YES	YES	YES	YES	YES	YES
time fixed	YES	YES	YES	YES	YES	YES	YES	YES
N	1668	1668	1960	1960	1668	1668	1960	1960
R^2	0.691	0.675	0.966	0.965	0.635	0.614	0.912	0.898

Note: This table examines the relationship between estimated scope economies measures and bank diversification when OBS activities are proxied by non-interest income. Panels A and B present results for asset and income diversification, respectively. Controls include ln E, $\ln\frac{p_1}{p_3}$, $\ln\frac{p_2}{p_3}$, assets and npl. Specifications include bank and year fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table 3-12 Robustness: results for the Fourier flexible function

Year	Obs.	Mean	Min	Max	S_C	S_R	S_V
2000	77	0.630	0.124	4.713	0.393	0.637	-0.401
2001	77	0.694	0.157	5.080	0.436	0.681	-0.423
2002	79	0.833	0.200	8.315	0.561	0.703	-0.431
2003	85	0.846	0.221	7.207	0.568	0.717	-0.439
2004	89	0.853	0.236	7.267	0.569	0.732	-0.448
2005	91	0.923	0.295	7.500	0.642	0.734	-0.453
2006	92	0.965	0.293	8.117	0.690	0.729	-0.455
2007	92	1.057	0.351	9.083	0.782	0.727	-0.452
2008	92	1.189	0.401	10.814	0.910	0.726	-0.447
2009	91	1.142	0.376	9.127	0.868	0.734	-0.460
2010	89	1.229	0.383	9.100	0.944	0.767	-0.482
2011	90	1.301	0.330	9.709	1.008	0.787	-0.494
2012	88	1.417	0.403	10.925	1.126	0.795	-0.504
2013	87	1.535	0.431	13.015	1.231	0.823	-0.519
2014	84	1.596	0.425	13.867	1.289	0.833	-0.525
2015	79	1.751	0.388	14.787	1.437	0.851	-0.538
2016	78	1.839	0.428	14.908	1.512	0.862	-0.535
2017	79	1.910	0.528	15.265	1.572	0.869	-0.531
2018	71	2.153	0.494	17.927	1.808	0.860	-0.514
2019	70	2.315	0.521	19.316	1.951	0.886	-0.522
2020	69	2.373	0.605	19.424	1.986	0.914	-0.527
Total	1749	1.332	0.124	19.424	1.035	0.776	-0.480

Note: This table presents the mean value of within-sample scope economies and their decomposed effects when bank costs are estimated by the Fourier flexible function.

Table 3-13 Robustness: regression results for Fourier flexible function

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Within-sample scope economies				Complementarity effect for within-sample			
loan ratio	2.052**				2.287**			
	(0.952)				(0.967)			
assset HHI		-1.848				-2.129*		
		(1.170)				(1.192)		
interest ratio			1.850**				1.888**	
			(0.887)				(0.901)	
income HHI				0.480				0.384
				(1.116)				(1.144)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
bank fixed	YES	YES	YES	YES	YES	YES	YES	YES
time fixed	YES	YES	YES	YES	YES	YES	YES	YES
N	1749	1749	1749	1749	1749	1749	1749	1749
R^2	0.468	0.465	0.471	0.461	0.438	0.434	0.440	0.428

Note: This table examines the relationship between within-sample scope economies, complementarity effect, and bank diversification when bank costs are estimated by the Fourier flexible function. Controls include ln E, $\ln\frac{p_1}{p_3}$, $\ln\frac{p_2}{p_3}$, assets and npl. Specifications include bank and year fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts $*$, $**$, $***$ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Figures

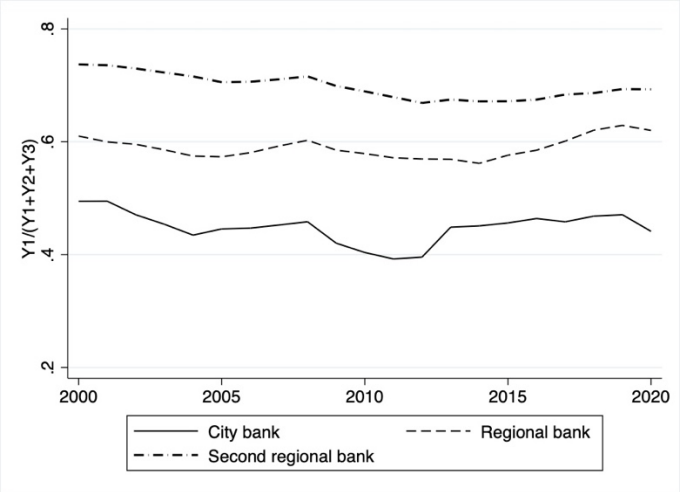

Figure 3-1 The average output share of loans over time, in %
Note: This figure shows the evolution of the share of loans on total outputs for different types of banks from 2000 to 2020. Y_1 – loans; Y_2 – securities; Y_3 – off-balance sheet activities.

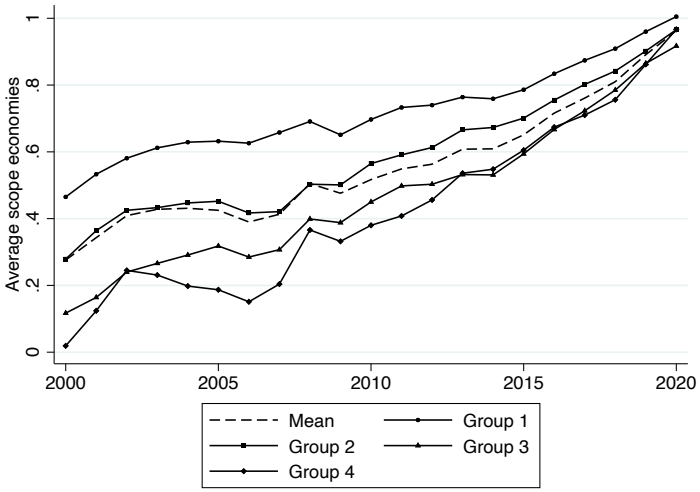

Figure 3-2 Average scope economies over time
Note: This figure shows the difference in estimated within-sample scope economies between the whole sample and four groups of banks of different sizes from 2000 to 2020. Groups 1 to 4 (small to large) are divided by bank assets in each year.

Appendix 1

1.1 Economies of diversification

Chavas and Kim (2010) consider a firm using *n* inputs to produce *m* outputs, where $\mathbf{y}=(y_1,\ldots,y_m) \in R_+^m$ is the vector of outputs, and $\mathbf{x} \in R_+^n$ is the vector of inputs. The price of inputs is given by $\mathbf{p} \in R_{++}^n$. $C(\mathbf{y},\mathbf{p})$ is the minimal cost that the firm chooses inputs for a given amount of feasible outputs.

Economies of diversification refer to whether the multiproduct firm would benefit or lose from reorganizing its production activities in a more specialized way. The reorganization involves breaking the firm into K specialized firms, $2 \le K \le m$. The original outputs $\mathbf{y}=(y_1,\ldots,y_m)$ are assumed to be strictly positive: $y_i>0$, i=1,…,m. For the kth specialized firm, the outputs are $\boldsymbol{y}^k = \left(y_1^k, \ldots, y_s^k\right)$, k=1,…,K, and the cost is $C(\mathbf{y}^k,\mathbf{p})$. Then, economies of diversification exist if

$$S \equiv \sum_{k=1}^{K} C(\boldsymbol{y}^k, \boldsymbol{p}) - C(\boldsymbol{y}, \boldsymbol{p}) > 0 \tag{A1}$$

Where $\sum_{k=1}^{K} \boldsymbol{y}^k = \boldsymbol{y}$ is satisfied to make the aggregate outputs of the K specialized firms equal to the outputs of the original firm. It means that the joint production by one multiproduct firm can save costs compared to the separated production with K specialization firms. In contrast, diseconomies of diversification exist if S is negative, suggesting a cost disadvantage in joint production. Similarly, an alternative relative measure can be used to reflect the proportional reduction in cost, that is

$$S' \equiv \left[\sum_{k=1}^{K} C(\boldsymbol{y}^k, \boldsymbol{p}) - \mathrm{C}(\boldsymbol{y}, \boldsymbol{p})\right] / C(\boldsymbol{y}, \boldsymbol{p}) \tag{A2}$$

Except for the cost function $C(\mathbf{y},\mathbf{p})$, S also depends on the specialization patterns, which describe the outputs of K specialized firms. For the output index $\boldsymbol{I}=\{1,\ldots,m\}$, consider a nontrivial partition $\{I_{A1},I_{A2},\ldots,I_{AK},I_B\}$ of $\boldsymbol{I}$, where $I_A=\{I_{A1},I_{A2},\ldots,I_{AK},I_B\}$, I_{AK} being the set of outputs that the kth firm is specializing in, k=1,…,K, and I_B being the set of output that no particular firm specializes in. The specialization pattern for the kth firm is considered:

$$y_i^k = y_i^+ = \beta_k y_i \quad \text{if } i \in I_{Ak} \tag{A3}$$

$$y_i^k = y_i^- = y_i(1-\beta_{k'})/(K-1) \quad \text{if i} \in I_{Ak'} \neq I_{Ak} \tag{A4}$$

$$y_i^k = y_i/k \quad \text{if } i \in I_B \tag{A5}$$

where $\beta_k \in (1/K, 1], k = 1, \ldots, K$. This pattern represents a reorganization of the original outputs into K specialized firms. The kth firm becomes more specialized in the production of outputs in the sets I_{AK}, and $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_K)$ represents the patterns of the specialization among the K firms. For example, we assume that banks use three inputs (n=3) to produce three outputs (m=3) in this paper. Considering each of the three banks (K=3) specializing in one output, thereby I_A={{1},{2},{3}} and I_B is empty. Given a specialization pattern **β,** the output for a specialized bank is $\beta_i y_i$, $i = 1,2,3$, for the specialized output i and $[(1-\beta_k)/2] * y_k$, $k \neq i$, for the other two non-specialized outputs. Therefore, if $\beta_i = 0.8$ for $i = 1,2,3$, bank 1 will produce 80% of the original output 1 and only produce 10% of the other two outputs, and so do other banks. It is easy to know that a larger β means a higher degree of specialization in the production of this output. When it comes to complete specialization, β is equal to 1, and it becomes the conventional definition of economies of scope.

1.2 Decomposition of economies of diversification

Given the definition of economies of diversification, Chavas and Kim (2010) further provide a framwork to decompose economies of scope. For the output vector $\boldsymbol{I}$={I_{A1},I_{A2},…,I_{AK},I_B}, let $\boldsymbol{y}_{Ak} = y_i: i \in I_{Ak}$, $\boldsymbol{y}_{A/Ak} = y_i: i \in I_A/I_{Ak}$where I_A/I_{Ak} denotes the set of outputs in I_A but not in I_{Ak}. The outputs of the original firm are $\boldsymbol{y}$={y_{A1},y_{A2},…,y_{AK},y_B}, and let $\boldsymbol{y}_{A,i:j} = (y_{Ai}, y_{A,i+1}, \ldots, y_{A,j-1}, y_{Aj})$ for i<j. Therefore, the output for the kth specialized firm $\mathbf{y}^k$ can be written as $\boldsymbol{y}^k = (\boldsymbol{y}_{Ak}^+, \boldsymbol{y}_{A/Ak}^-, y_B/K)$, where $y_{Ak}^+ = \{y_i^+: i \in I_{Ak}\}$, and $y_{A/Ak}^- = \{y_i^-: i \in T_A/I_{Ak}\}$. In other words, y_{Ak}^+ contains the outputs that the bank specializes in, while the production of non-specialized outputs is shown in $y_{A/Ak}^-$.

They assume that the cost function can be written as $C(\mathbf{y},\mathbf{p})=C_v(\mathbf{y},\mathbf{p})+C_f(\mathbf{y},\mathbf{p})$, where C_v is the variable cost which is continuous everywhere on R_m^+, and C_f is the fixed cost function which is a step function exhibiting possible discontinuities at $\mathbf{y}=\mathbf{0}$. Economies of diversification can be decomposed into:

$$S \equiv S_C + S_R + S_V + S_f \tag{A6}$$

$$S_C \equiv \sum_{k=1}^{K-1} \{ \int_{y_{Ak}^-}^{y_{Ak}^+} \frac{\partial C_v}{\partial \gamma} (\boldsymbol{y}_{A,1:k-1}^-, \gamma, \boldsymbol{y}_{A,1:k-1}^-, \boldsymbol{y}_B/K, \boldsymbol{p}) d\gamma - \int_{y_{Ak}^-}^{y_{Ak}^+} \frac{\partial C_v}{\partial \gamma} (\boldsymbol{y}_{A,1:k-1}^-, \gamma, \boldsymbol{y}_{A,k+1:K}^+, \boldsymbol{y}_B/K, \boldsymbol{p}) d\gamma \} \quad \text{(A7)}$$

$$S_R \equiv KC(\boldsymbol{y}/K, \boldsymbol{p}) - C(\boldsymbol{y}, \boldsymbol{p}) \quad \text{(A8)}$$

$$S_v \equiv C(\boldsymbol{y}_A^+, \boldsymbol{y}_B/K, \boldsymbol{p}) + (K-1)C(\boldsymbol{y}_A^-, \boldsymbol{y}_B/K, \boldsymbol{p}) - KC(\boldsymbol{y}/K, \boldsymbol{p}) \quad \text{(A9)}$$

$$S_f \equiv \sum_{k=1}^{K} C_f\left(\boldsymbol{y}_{Ak}^+, \boldsymbol{y}_{A/Ak}^-, \boldsymbol{y}_B/K, \boldsymbol{p}\right) - C_f(\boldsymbol{y}_A^-, \boldsymbol{y}_B/K, \boldsymbol{p}) - (K-1)C_f(\boldsymbol{y}_A^-, \boldsymbol{y}_B/K, \boldsymbol{p}) \quad \text{(A10)}$$

where S_C describes how $\boldsymbol{y}_{A/Ak}$ affects the marginal cost of $\boldsymbol{y}_{Ak}$and reflects the presence of complementarity among outputs in $\boldsymbol{y}_A$; S_R measures the returns to the scale; S_V reflects the convexity/concavity property of the cost function C(**y**, **p**) in **y**; Sf reflects the effects of fixed costs on diversification economies.

Further, they derive two propositions on full or partial specialization.

Proposition 1

*Assume that C(**0**, **p**)=0. In the case of complete specialization (where β_k=1 for all k, and I_B=∅), then S_R+S_V=0.*

Proposition 2

Assume y_i>0, i=1, …, m. Then, partial specialization (where 1/K<β_k<1 for all k) implies that S_f=0.

Proposition 1 shows that the scale and convexity effects will cancel each other under complete specialization. If there is also no fixed cost (C_f=0), economies of diversification are equal to the complementarity effect and economies of scope, which explains why complementarity can be used to measure economies of scope. Proposition 2 shows that the fixed effect equals zero when 1/K<β_k<1, for all k, is satisfied. This is more general in application and enables us to calculate the complementarity effect indirectly. A more detailed proof process is available in Chavas and Kim (2010).

Appendix 2

The results of the 2SLS regression are shown as follows:

Table A3-1 2SLS regression results for the relationship between diversification and scope economies

Panel A: asset diversification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Within-sample scope economies		Economies of diversification (β=0.8)		Complementarity effect for within-sample		Complementarity effect (β=0.8)	
loan ratio (instrumented)	0.995***		0.328***		1.186***		0.407***	
	(0.133)		(0.032)		(0.161)		(0.021)	
asset HHI (instrumented)		-1.064***		-0.361***		-1.255***		-0.480***
		(0.186)		(0.047)		(0.224)		(0.032)
ln E	-0.308***	-0.315***	-0.189***	-0.192***	-0.135***	-0.143***	-0.056***	-0.061***
	(0.020)	(0.020)	(0.008)	(0.007)	(0.019)	(0.020)	(0.005)	(0.004)
$\ln\frac{p_1}{p_3}$	-0.055***	-0.054***	-0.052***	-0.052***	-0.015	-0.014	-0.012***	-0.011***
	(0.018)	(0.018)	(0.003)	(0.003)	(0.017)	(0.017)	(0.002)	(0.002)
$\ln\frac{p_2}{p_3}$	0.005	0.000	0.096***	0.094***	-0.039	-0.045*	0.019***	0.016***
	(0.023)	(0.023)	(0.005)	(0.005)	(0.024)	(0.024)	(0.003)	(0.003)
assets	0.360***	0.353***	0.030**	0.028**	0.429***	0.420***	0.006	0.002
	(0.058)	(0.062)	(0.013)	(0.013)	(0.062)	(0.066)	(0.007)	(0.008)
npl	0.257	0.136	0.053	0.012	0.262	0.121	0.053	-0.009
	(0.192)	(0.221)	(0.069)	(0.062)	(0.176)	(0.202)	(0.063)	(0.054)
bank fixed	YES	YES	YES	YES	YES	YES	YES	YES
time fixed	YES	YES	YES	YES	YES	YES	YES	YES
N	1636	1636	1963	1963	1636	1636	1963	1963
Panel B: income diversification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Within-sample scope economies		Economies of diversification (β=0.8)		Complementarity effect for within-sample		Complementarity effect (β=0.8)	
interest ratio (instrumented)	0.332**		0.149***		0.433**		0.167***	
	(0.160)		(0.045)		(0.170)		(0.042)	
Income HHI (instrumented)		-0.222		0.005		-0.202		-0.075
		(0.259)		(0.089)		(0.286)		(0.082)
ln E	-0.298***	-0.300***	-0.187***	-0.186***	-0.123***	-0.125***	-0.055***	-0.054***
	(0.021)	(0.020)	(0.007)	(0.008)	(0.023)	(0.022)	(0.004)	(0.005)
$\ln\frac{p_1}{p_3}$	-0.062***	-0.057***	-0.055***	-0.053***	-0.024	-0.017	-0.014***	-0.012***
	(0.017)	(0.019)	(0.003)	(0.003)	(0.016)	(0.018)	(0.002)	(0.002)
$\ln\frac{p_2}{p_3}$	0.019	0.016	0.103***	0.102***	-0.021	-0.026	0.027***	0.027***
	(0.024)	(0.027)	(0.006)	(0.006)	(0.025)	(0.030)	(0.005)	(0.006)
assets	0.371***	0.381***	0.035**	0.040***	0.440***	0.455***	0.013	0.015
	(0.062)	(0.066)	(0.014)	(0.015)	(0.068)	(0.071)	(0.011)	(0.013)
npl	0.383	0.454*	0.115**	0.146**	0.402	0.501*	0.134**	0.168***
	(0.295)	(0.269)	(0.057)	(0.067)	(0.291)	(0.257)	(0.053)	(0.061)
bank fixed	YES	YES	YES	YES	YES	YES	YES	YES
time fixed	YES	YES	YES	YES	YES	YES	YES	YES
N	1636	1636	1963	1963	1636	1636	1963	1963

Note: This table examines the relationship between estimated scope economies measures and bank diversification that is instrumented by lagged diversification variables. Panels A and B present results for asset and income diversification, respectively. Specifications include bank and year fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Reference

Abedifar, P., P. Molyneux and A. Tarazi (2018), Non-interest income and bank lending, *Journal of Banking & Finance,* 87**,** 411-26.

Aigner, D., C. K. Lovell and P. Schmidt (1977), Formulation and estimation of stochastic frontier production function models, *Journal of Econometrics,* 6**,** 21-37.

Altunbas, Y. and P. Molyneux (1996), Economies of scale and scope in European banking, *Applied Financial Economics,* 6**,** 367-75.

Amici, A., F. Fiordelisi, F. Masala, O. Ricci and F. Sist (2013), Value creation in banking through strategic alliances and joint ventures, *Journal of Banking & Finance,* 37**,** 1386-96.

Baele, L., O. De Jonghe and R. V. Vennet (2007), Does the Stock Market Value Bank Diversification, *Journal of Banking & Finance,* 31**,** 1999-2023.

Baumol, W. J., J. C. Panzar and R. D. Willig (1982), Contestable markets and the theory of industry structure: Harcourt College Pub.

Beccalli, E., M. Anolli and G. Borello (2015), Are European banks too big? Evidence on economies of scale, *Journal of Banking & Finance,* 58**,** 232-46.

Beccalli, E. and L. Rossi (2020), Economies or diseconomies of scope in the EU banking industry?, *European Financial Management,* 26**,** 1261-93.

Belotti, F. and G. Ilardi (2018), Consistent inference in fixed-effects stochastic frontier models, *Journal of Econometrics,* 202**,** 161-77.

Benston, G. J., A. N. Berger, G. A. Hanweck and D. B. Humphrey (1983), Economies of scale and scope in banking. Board of Governors of the Federal Reserve System (US).

Berger, A. N., G. A. Hanweck and D. B. Humphrey (1987), Competitive viability in banking: Scale, scope, and product mix economies, *Journal of monetary economics,* 20**,** 501-20.

Berger, A. N., I. Hasan and M. Zhou (2010), The effects of focus versus diversification on bank performance: Evidence from Chinese banks, *Journal of Banking & Finance,* 34**,** 1417-35.

Berger, A. N., D. B. Humphrey and L. B. Pulley (1996), Do consumers pay for one-stop banking? Evidence from an alternative revenue function, *Journal of Banking & Finance,* 20**,** 1601-21.

Berger, A. N. and L. J. Mester (1997), Inside the black box: What explains differences in the efficiencies of financial institutions?, *Journal of Banking & Finance,* 21**,** 895-947.

Berger, A. N. and L. J. Mester (2003), Explaining the dramatic changes in performance of US banks: technological change, deregulation, and dynamic changes in competition, *Journal of Financial Intermediation,* 12**,** 57-95.

Bolt, W. and D. Humphrey (2010), Bank competition efficiency in Europe: A frontier approach, *Journal of Banking & Finance,* 34**,** 1808-17.

Calmès, C. and R. Théoret (2010), The impact of off-balance-sheet activities on banks returns: An application of the ARCH-M to Canadian data, *Journal of Banking & Finance,* 34**,** 1719-28.

Cavallo, L. and S. P. Rossi (2001), Scale and scope economies in the European banking systems, *Journal of Multinational Financial Management,* 11**,** 515-31.

Chavas, J.-P. and K. Kim (2010), Economies of diversification: A generalization and decomposition of economies of scope, *International Journal of Production Economics,* 126**,** 229-35.

Chen, Y.-Y., P. Schmidt and H.-J. Wang (2014), Consistent estimation of the fixed effects stochastic frontier model, *Journal of Econometrics,* 181**,** 65-76.

Chiorazzo, V., C. Milani and F. Salvini (2008), Income diversification and bank performance: Evidence from Italian banks, *Journal of Financial Services Research,* 33**,** 181-203.

Clark, J. A. (1988), Economies of scale and scope at depository financial institutions: A review of the literature, *Federal Reserve Bank of Kansas City Economic Review,* 73**,** 16-33.

Clark, J. A. and T. F. Siems (2002), X-efficiency in banking: Looking beyond the balance sheet, *Journal of Money, Credit and Banking***,** 987-1013.

Davies, R. and B. Tracey (2014), Too big to be efficient? The impact of implicit subsidies on estimates of scale economies for banks, *Journal of Money, Credit and Banking,* 46**,** 219-53.

Deyoung, R. and T. Rice (2004), Noninterest income and financial performance at US commercial banks, *Financial review,* 39**,** 101-27.

Eder, A. (2018), Measuring and decomposing economies of diversification: An application to biogas-fuelled cogeneration plants in Austria, *International Journal of Production Economics,* 204**,** 421-32.

Elsas, R., A. Hackethal and M. Holzhäuser (2010), The anatomy of bank diversification, *Journal of Banking & Finance,* 34**,** 1274-87.

Feng, G. and A. Serletis (2009), Efficiency and productivity of the US banking industry, 1998–2005: Evidence from the Fourier cost function satisfying global regularity conditions, *Journal of Applied Econometrics,* 24**,** 105-38.

Feng, G. and X. Zhang (2014), Returns to scale at large banks in the US: A random coefficient stochastic frontier approach, *Journal of Banking & Finance,* 39**,** 135-45.
Gaganis, C. and F. Pasiouras (2013), Financial supervision regimes and bank efficiency: International evidence, *Journal of Banking & Finance,* 37**,** 5463-75.
Gallant, A. R. (1981), On the bias in flexible functional forms and an essentially unbiased form: the Fourier flexible form, *Journal of Econometrics,* 15**,** 211-45.
Gallant, A. R. (1982), Unbiased determination of production technologies, *Journal of Econometrics,* 20**,** 285-323.
Gilligan, T., M. Smirlock and W. Marshall (1984), Scale and scope economies in the multi-product banking firm, *Journal of monetary economics,* 13**,** 393-405.
Gilligan, T. W. and M. L. Smirlock (1984), An empirical study of joint production and scale economies in commercial banking, *Journal of Banking & Finance,* 8**,** 67-77.
Greene, W. (2005a), Fixed and random effects in stochastic frontier models, *Journal of Productivity Analysis,* 23**,** 7-32.
Greene, W. (2005b), Reconsidering heterogeneity in panel data estimators of the stochastic frontier model, *Journal of Econometrics,* 126**,** 269-303.
Guerry, N. and M. Wallmeier (2017), Valuation of diversified banks: New evidence, *Journal of Banking & Finance,* 80**,** 203-14.
Harimaya, K. (2008), Impact of nontraditional activities on scale and scope economies: A case study of Japanese regional banks, *Japan and the World Economy,* 20**,** 175-93.
Hughes, J. P. and L. J. Mester (1993), A quality and risk-adjusted cost function for banks: Evidence on the "too-big-to-fail" doctrine, *Journal of Productivity Analysis,* 4**,** 293-315.
Hughes, J. P. and L. J. Mester (1998), Bank capitalization and cost: Evidence of scale economies in risk management and signaling, *Review of economics and statistics,* 80**,** 314-25.
Hughes, J. P. and L. J. Mester (2013), Who said large banks don't experience scale economies? Evidence from a risk-return-driven cost function, *Journal of Financial Intermediation,* 22**,** 559-85.
Humphrey, D., M. Willesson, G. Bergendahl and T. Lindblom (2006), Benefits from a changing payment technology in European banking, *Journal of Banking & Finance,* 30**,** 1631-52.
Humphrey, D. B. (1985), Costs and scale economies in bank intermediation, *Handbook for banking strategy***,** 745-83.
Hunter, W. C., S. G. Timme and W. K. Yang (1990), An examination of cost subadditivity and multiproduct production in large US banks, *Journal of Money, Credit and Banking,* 22**,** 504-25.
Jagtiani, J., A. Nathan and G. Sick (1995), Scale economies and cost complementarities in commercial banks: On- and off-balance-sheet activities, *Journal of Banking & Finance,* 19**,** 1175-89.
Jiraporn, P., Y. S. Kim, W. N. Davidson and M. Singh (2006), Corporate governance, shareholder rights and firm diversification: An empirical analysis, *Journal of Banking & Finance,* 30**,** 947-63.
Karim, D., I. Liadze, R. Barrell and E. P. Davis (2013), Off-balance sheet exposures and banking crises in OECD countries, *Journal of Financial Stability,* 9**,** 673-81.
Kim, H. Y. (1986), Economies of scale and economies of scope in multiproduct financial institutions: Further evidence from credit unions, *Journal of Money, Credit and Banking,* 18**,** 220-26.
Kumbhakar, S. C., C. F. Parmeter and V. Zelenyuk (2020), Stochastic frontier analysis: Foundations and advances I, *Handbook of production economics***,** 1-40.
Laeven, L. and R. Levine (2007), Is There a Diversification Discount in Financial Conglomerates, *Journal of Financial Economics,* 85**,** 331-67.
Lozano-Vivas, A. and F. Pasiouras (2010), The impact of non-traditional activities on the estimation of bank efficiency: International evidence, *Journal of Banking & Finance,* 34**,** 1436-49.
Lozano-Vivas, A. and F. Pasiouras (2014), Bank productivity change and off-balance-sheet activities across different levels of economic development, *Journal of Financial Services Research,* 46**,** 271-94.
Malikov, E. and V. Hartarska (2018), Endogenous scope economies in microfinance institutions, *Journal of Banking & Finance,* 93**,** 162-82.
Mccord, R. and E. S. Prescott (2014), The financial crisis, the collapse of bank entry, and changes in the size distribution of banks, *FRB Richmond Economic Quarterly,* 100**,** 23-50.
Mester, L. J. (1987), A multiproduct cost study of savings and loans, *The Journal of Finance,* 42**,** 423-45.
Mester, L. J. (1991), Agency costs among savings and loans, *Journal of Financial Intermediation,* 1**,** 257-78.
Mester, L. J. (1992), Traditional and nontraditional banking: an information-theoretic approach, *Journal of Banking & Finance,* 16**,** 545-66.
Mester, L. J. (1996), A study of bank efficiency taking into account risk-preferences, *Journal of Banking & Finance,* 20**,** 1025-45.
Mitchell, K. and N. M. Onvural (1996), Economies of scale and scope at large commercial banks: Evidence from the Fourier flexible functional form, *Journal of Money, Credit and Banking,* 28**,** 178-99.
Murray, J. D. and R. W. White (1983), Economies of scale and economies of scope in multiproduct financial

institutions: A study of British Columbia credit unions, *The Journal of Finance,* 38**,** 887-902.
Nguyen, T. L. A. (2018), Diversification and bank efficiency in six ASEAN countries, *Global Finance Journal,* 37**,** 57-78.
Noulas, A. G., S. M. Miller and S. C. Ray (1993), Regularity conditions and scope estimates: the case of large-sized US banks, *Journal of Financial Services Research,* 7**,** 235-48.
Panzar, J. C. and R. D. Willig (1981), Economies of scope, *The American economic review,* 71**,** 268-72.
Pulley, L. B. and Y. M. Braunstein (1992), A composite cost function for multiproduct firms with an application to economies of scope in banking, *The Review of Economics and Statistics***,** 221-30.
Pulley, L. B. and D. B. Humphrey (1993), The role of fixed costs and cost complementarities in determining scope economies and the cost of narrow banking proposals, *Journal of Business***,** 437-62.
Rogers, K. E. (1998), Nontraditional activities and the efficiency of US commercial banks, *Journal of Banking & Finance,* 22**,** 467-82.
Sawada, M. (2013), How does the stock market value bank diversification? Empirical evidence from Japanese banks, *Pacific-Basin Finance Journal,* 25**,** 40-61.
Schmid, M. M. and I. Walter (2009), Do financial conglomerates create or destroy economic value?, *Journal of Financial Intermediation,* 18**,** 193-216.
Sealey Jr, C. W. and J. T. Lindley (1977), Inputs, outputs, and a theory of production and cost at depository financial institutions, *The Journal of Finance,* 32**,** 1251-66.
Stein, J. C. (1997), Internal capital markets and the competition for corporate resources, *The Journal of Finance,* 52**,** 111-33.
Stiroh, K. J. (2004), Diversification in banking: Is noninterest income the answer?, *Journal of Money, Credit and Banking***,** 853-82.
Stiroh, K. J. and A. S. Rumble (2006), The Dark Side of Diversification: The Case of US Financial Holding Companies, *Journal of Banking and Finance,* 30**,** 2131-61.
Vennet, R. V. (2002), Cost and profit efficiency of financial conglomerates and universal banks in Europe, *Journal of Money, Credit and Banking***,** 254-82.
Wang, H.-J. and C.-W. Ho (2010), Estimating fixed-effect panel stochastic frontier models by model transformation, *Journal of Econometrics,* 157**,** 286-96.
Wheelock, D. C. and P. W. Wilson (2001), New evidence on returns to scale and product mix among US commercial banks, *Journal of monetary economics,* 47**,** 653-74.
Wheelock, D. C. and P. W. Wilson (2012), Do large banks have lower costs? New estimates of returns to scale for US banks, *Journal of Money, Credit and Banking,* 44**,** 171-99.
Zhang, J. and E. Malikov (2022), Off-balance sheet activities and scope economies in US banking, *Journal of Banking & Finance,* 141**,** 106534.

Chapter 4 Bank complexity, performance, and governance: Evidence from Japan

Abstract: This paper examines the relationship between bank complexity and performance in Japan, where complexity is defined from organizational, business, and geographic dimensions. I find that the Japanese market values only business complexity, but there is no strong and consistent evidence for a risk-decline effect. As better governance arrangements are expected to mitigate the adverse effects of complexity, such as agency costs, I further investigate the impacts of governance on bank performance. The results show higher board shareholding, large board size, and few independent directors can reduce bank risk but have little effect on market value. However, these governance arrangements play a minor role in the impacts of complexity on performance. My results also suggest that diversification benefits, lower funding costs, and opacity effects can explain complexity effects, and small banks face more challenges when adopting a complexity strategy.

Keywords: bank complexity; market value; bank risk, governance

4.1. Introduction

The bank diversification issue has attracted much attention from researchers worldwide since the 2000s (Zouaoui and Zoghlami, 2023). While many researchers seek to understand whether diversification enhances bank performance and its underlying mechanisms, the focus often remains on the group as a whole, neglecting the methods and processes of how banks diversify their business, especially in the context of the deregulation of banking organizations. This oversight is evident in the choice of bank diversification measures. Typically, bank diversification is defined using metrics such as the non-interest income ratio (NII) or the share of non-loan assets to total earning assets (Laeven and Levine, 2007). However, these indicators merely quantify the extent to which bank groups are involved in or generate income from non-traditional lending businesses, providing limited insights into the organizational strategies employed by banks to achieve such diversification. A common way for banks to engage in new businesses or regions is through M&A and establishing new subsidiaries, especially after the deregulation of bank holding companies (BHCs) and financial holding companies (FHCs). For example, Avraham et al. (2012) present that the number of separate legal entities within each BHC in the United States has increased dramatically compared to the 1990s. The passage of the Gramm–Leach–Bliley Act (GLBA) of 1999 enabled a BHC to register as an FHC to engage in a broad range of financial activities, such as securities underwriting and insurance underwriting. Expanding business scope or cross-border entry through subsidiaries offers advantages like limited liability (Dell'Ariccia and Marquez, 2010), opaque transmission of information (Kahn and Winton, 2004), and mutual rescue (Luciano and Wihlborg, 2018). This leads to more complex organizational structures in banks and BHCs. Moreover, in the context of elucidating the potential adverse effects of diversification, conventional explanations often invoke agency costs or the challenges stemming from a lack of expertise when venturing into new areas. Nevertheless, without delving into the organizational structure of banking groups, we cannot directly discern whether a higher non-interest income (NII) is associated with increased incentives for empire-building or a multitude of non-banking or non-financial involvements. All these issues call for further studies on the organizational structure of banks and how bank complexity affects bank performance.

In addition, research on bank complexity has multiple implications for policymakers and regulators. First, bank complexity is vital for identifying Global Systemically Important Financial Institutions(G-SIFIs). The 2008 financial crisis highlights the issue of too-big-to-fail (TBTF), which led to a global consensus to impose stricter regulations on institutions whose

failure would trigger a financial crisis. According to the chapter of SCO40 in Basel Framework, complexity, including business, structural, and operational complexity, is recognized as positively correlated with the systemic impact of a bank's distress and is assigned a weight of 20% in assessing the systemic importance. Second, complexity is considered a source of bank risk and, therefore, a key policy concern. Although the related studies are still limited, the empirical results that more complex banks tend to have higher risk have been found in the U.S. (Chernobai et al., 2021, Correa and Goldberg, 2022), Germany (Martynova and Vogel, 2022), and Hong Kong (Ho et al., 2022). Understanding the impact of bank complexity can help the authorities formulate precise banking regulations for different banks. Third, complexity is crucial information for post-failure resolution. It is essential for the regulator to know the bank's complexity to assess the difficulty of post-failure resolution and quickly disentangle the subsidiaries when a bank fails (Flood et al., 2020).

However, the bank complexity issue needs to be more researched. Previous literature primarily concentrates on measuring bank complexity and its impact on bank risk. The term "complexity" is used in various official documents and papers, but its interpretation varies across contexts, contributing to the ambiguity in defining bank complexity. In a regulatory context, complexity is measured by the notional amount of over-the-counter (OTC) derivatives, Level 3 assets, trading and available-for-sale securities (Board, 2013), which is only related to the opacity of balance sheet and off-balance sheet assets of banks (Buch and Goldberg, 2022). In contrast, academics usually measure complexity regarding bank subsidiaries, such as their organizational structure, business, or geographic scope (see more in Correa and Goldberg, 2022). More importantly, recent studies focus on the correlation between bank complexity and risk-taking. For example, the *Journal of Banking and Finance* featured six papers that delved into bank complexity in 2022, all of which addressed the impact of complexity on bank risk. This leaves a huge gap in the literature on how complexity affects performance other than risk, such as profitability or market value.

This paper also addresses the governance of Japanese banks. Previous literature often attributes agency problems to explain the adverse impact of complexity. When a bank expands into new business areas or regions, the parent company tends to be less efficient in managing and supervising its subsidiaries, which can lead to moral hazard. In addition, it also intensifies among the parent and affiliates, as well as among different affiliates. Therefore, stronger governance arrangements are expected to mitigate the adverse effects when banks become more complex. This holds significance for Japanese banks, as limited studies have delved into their governance structures compared to the extensive research conducted in the US or Europe.

As such, this paper attempts to analyze the relationship between bank complexity, market value, risk, and bank governance, exploring several effective channels for understanding the mechanism.

For several reasons, the Japanese banking industry is an apt sample for my study. First, Japan has a more bank-intermediated financial system than other developed markets. According to Uchida and Udell (2019), banks in Japan held nearly 23% of the country's financial assets in 2017. Additionally, these banks play a pivotal role in financing corporate and government sectors, and half of the financial assets held by the household are deposits. In such a system, it is anticipated that banks will attract greater market attention, rendering the stock market more sensitive to any strategic shifts by banks. Second, the deregulation of BHC in 1998 has potentially incentivized banks to undertake more proactive measures to expand, introducing additional variability to banks' organizational structures. Like the deregulation in the US, it allows Japanese banks to enter other financial businesses, such as investment banking and insurance, through a holding company structure. BHCs have risen from 7 in 2005 to 23 in 2021, with a notable acceleration in recent years. A noteworthy observation is the evolving purpose behind establishing a BHC, transitioning from merger-driven to business expansion-driven. The increasing number of independent banks transitioning to BHCs suggests a potential positive inclination toward complexity strategies, rendering this study more practically relevant. Third, banks in Japan are obligated to disclose information about their subsidiaries in their financial reports, providing a comprehensive data set for analysis.

Using a sample of 1845 bank-year observations for 114 banks from 2000 to 2020, I examine the relationship between bank complexity and performance, considering the moderating effects of governance. Following Correa and Goldberg (2022) and Martynova and Vogel (2022), complexity metrics are constructed based on the number of subsidiaries in three dimensions: organizational, operational, and geographic. Organizational complexity is measured by the number of separate legal entities in a group, while business and geographic complexity involve four variables each, capturing a bank's involvement in diverse industries, regions, and diversified distribution. To simplify complexity measures, the study employs principal component analysis, extracting a single principal component to represent the four business or geographic complexity variables. The assessment of bank performance incorporates Tobin's Q as a proxy for market value and encompasses three types of bank risk: total risk, systematic risk, and insolvency risk, providing a comprehensive examination of the impact of bank complexity. In terms of bank governance, I am mainly concerned about the shareholding and

composition of the board, as the board is not only a decision-making entity but plays a crucial role in performing supervisory functions on behalf of shareholders.

The first finding of the baseline regression indicates that business complexity can enhance a bank's market value, but there is no strong evidence that bank complexity increases or decreases bank risk-taking. The empirical results on market value suggest that only business complexity has a significant positive effect. Markets appear to respond positively to organizational and geographic complexity, but not significantly. In terms of bank risk, I find that bank complexity has a weak negative effect on market-based risk measures. For example, business complexity correlates with a decrease in the variability of stock returns. Furthermore, the risk-decline effect becomes more significant when considering the dynamic of dependent variables. On the contrary, complexity measures exhibit a positive correlation concerning insolvency risk, implying that complexity is associated with an increase in insolvency risk. The opposing effects of complexity on various risk measures suggest a potential trade-off in risk management.

The second finding reveals that higher board shareholding, larger boards, and fewer independent directors are associated with a reduction in bank risk, but these governance arrangements cannot mitigate possible adverse effects of the complexity. I do not find that the market values bank governance, while it does affect bank risk-taking. However, better governance associated with a risk-decline effect does not enhance the positive effect of complexity effects on market value or the negative effect on risk measures. Conversely, larger boards are found to diminish the impact of complexity on market value, and higher board shareholding encourages risk-taking in more complex banks. These findings suggest that better governance structures may not effectively mitigate the adverse effects of complexity and, at times, may even introduce negative effects.

Next, I examine several channels that may explain the impact of complexity on bank performance. The first one is the bank diversification channel. I find that complex banks tend to be more diversified in income sources. This may explain the positive effects on market value and some negative effects on risk as diversification is found to be value-enhancing and risk-declining in Japan (Sawada, 2013). The second one is the funding costs channel. Banks with higher organizational and business complexity have lower funding costs, which are more valuable in the market and dampen risk-taking incentives. The third one is the opacity effect channel. I find that business complex banks are more opaque, while geographic complex banks are less opaque. Increased bank opacity tends to encourage risk-taking behaviors, thereby explaining the heightened insolvency risk observed.

Finally, I consider the heterogeneous impact of bank size on the effects of complexity and governance, as smaller banks are more likely to enjoy fewer benefits but face higher risks as they become more complex. The results are consistent with this expectation, revealing that organizational and geographic complexity fails to yield significant benefits to small banks but poses greater risks. On the other hand, the positive effects of business complexity on Tobin's Q are more pronounced for large banks but at the cost of increased risk.

This paper contributes to the existing literature in three aspects. Firstly, it adds to the broader literature on the relationship between bank complexity and performance, offering new insights within the context of Japan. While complexity studies have been conducted in various countries such as the U.S., Germany, Hong Kong, Italy, and Spain (Buch and Goldberg, 2022), there is a notable absence of related studies within the Japanese banking industry. In addition, this study marks the first exploration of complexity effects on the market value in the Japanese banking sector, thus enriching our understanding of bank complexity. Secondly, it advances research on the governance of Japanese banks. While previous studies like Nakano and Nguyen (2012) and Aman and Nguyen (2012) have delved into the composition of boards for Japanese firms, few have specifically considered Japanese banks. This study reveals a significant correlation between bank governance and risk, providing new evidence for understanding Japanese bank behaviors. Lastly, the results contribute new evidence to the ongoing debate on the benefits of bank diversification in Japan. Although the diversification effect is still debatable, most studies have shown that it has positively impacted the Japanese banking sector industry (Sawada, 2013, Harimaya and Ozaki, 2021). This paper shows that business complexity can increase bank value, which is consistent with the diversification benefits found in Japan.

This paper is structured as follows. In section 2, I present the previous literature about measuring bank complexity and the mechanism behind the complexity effects, then develop hypotheses. Section 3 shows the data, variables, and methodology used in the empirical analysis, and section 4 presents the main results for baseline regressions and the robustness tests. In section 5, I discuss three possible channels through which complexity affects bank performance and consider the heterogeneity between banks of different sizes. Section 6 concludes.

4.2. literature review and hypothesis development

This section first describes the metrics adopted in prior literature in measuring bank complexity and then describes the possible mechanisms behind the impact of complexity on bank performance. We also address the problem of limited studies on performance indicators other than risk.

4.2.1 The metrics of bank complexity

The term "bank complexity" initially lacked a widely accepted definition and was mainly used to describe the differences in the organizational structure of different banks. For example, Strahan and Weston (1998) posit in their analysis that multi-bank banking companies are more complex than single-bank, and among multi-bank companies, organizational complexity increases from single-state to multi-state banking companies. This implies a major aspect of complexity: banking companies are more complex if they have more bank subsidiaries.

Large financial conglomerates are no longer rare as more banks expand their business scope to other financial sectors, such as securities and insurance, and venture into foreign markets. This raises concerns about the impact on systemic risk if they fail. The Financial Stability Forum (FSF) introduced the term "large complex financial institutions (LCFIs)[24]" to address the issue of the "too Big to Save" (Hüpkes, 2005). In this period, more meanings have been added to complexity. Expanding into nonbanking business and international operations is considered as an important perspective to describe a complex banking organization. Herring and Carmassi (2012) discuss the history and situation of LCFIs in 2007 in detail. They use the number of majority-owned subsidiaries as an indicator to describe the corporate complexity of banks and also analyze the share of foreign subsidiaries, foreign income, and the concentration of business line revenues. Avraham et al. (2012) focus on the organizational complexity of BHCs in the U.S., measured by the number of subsidiaries. Their results show that complexity, size, and scope have largely increased over the past decades, and total assets positively correlate to bank complexity. Another related study conducted by Cetorelli et al. (2014) measures organizational complexity by the extent to which a BHC acquires entities operating in different industries of the financial sector through a large sample of acquisition activity of entities. They find that BHCs are expanding their business scope through different types of subsidiaries, thus becoming less bank-centric.

[24] After the 2008 financial crisis, the policymakers have formed a consensus on identifying "Global Systemically Important Financial Institutions." The Basel Committee Banking Supervision published a consultative document on the methodology for assessing and identifying G-SIFIs in 2011, and the list of G-SIFIs is updated every year. The term "LCFIs" is gradually replaced by G-SIFIs.

Cetorelli and Goldberg (2014) propose three different aspects of bank complexity: organizational complexity (the number of subsidiaries), business complexity (business types of subsidiaries), and geographic complexity (locations of subsidiaries). They emphasized that complexity cannot be equated with bank size, as there is much more complexity that cannot be explained by size alone. Although the variables employed in Cetorelli and Goldberg (2014) may not sufficiently capture variation in complexity, the concept of the triple complexity dimension has gained broad acceptance among subsequent studies (see more in Correa and Goldberg, 2022, Marinelli et al., 2022, Argimón and Rodríguez-Moreno, 2022).

However, complexity can easily be confused with another term, "diversification". Indeed, there are some similarities between diversification and complexity in terms of meaning and research practice. It is natural to assume that banks that are more diversified in business or geography tend to be more complex, as this is what we have seen in the real economy. For example, Ho et al. (2022) and Chernobai et al. (2021) employed commonly used diversification indicators to describe bank complexity. While not explicitly addressed in previous studies, a notable distinction between the two terms is that complexity focuses on the corporate structure of a banking company, or in other words, the connection with subsidiaries[25]. This is because the complexity issue arises from the supervision of banks, where the authorities have to deal with the legal entities that would require some form of bankruptcy or resolution process in cases of insolvency (Carmassi and Herring, 2016).

There are other methods to measure complexity from different perspectives. Cao and Juelsrud (2022) argue that balance sheet opacity is a form of bank complexity that stems from the scarcity of information for assessing the quality of bank assets and the difficulty of processing public information. They use the proportion of off-balance sheet activities and available-for-sale trading assets as proxies for these two types of opacity. Liu et al. (2016) consider two dimensions of business complexity. The first dimension relates to the diversity of business activities, while the second dimension relates to the uniqueness or rarity of these activities. A bank is considered complex if it can offer a wide range of products or offers unique products that are not typically available from most banks. In addition, Flood et al. (2020) apply a topological approach to measure organizational complexity based on corporate control hierarchy. They find that their measures correlate highly with the complexity metrics used to identify G-SIFIs.

[25] The difference in metrics between business and geographic complexity and diversification is that complexity studies rarely use accounting data to measure complexity and they focus more on the bank's subsidiaries than its branches.

4.2.2 Complexity, bank value, and risk

Complex banks tend to have an intricate organizational structure, with many subsidiaries participating in different types of business in the domestic or foreign markets. The internal capital market within a group can enhance the efficiency of conglomerate investments and relax the credit constraints of bank affiliates since it reduces information asymmetries between project managers and investors, and the parent company could actively allocate funds from poor projects to more promising projects (Stein, 1997, Campello, 2002). Moreover, the share of internal funds, technology, and information undoubtedly positively impacts group performance as they can enjoy the benefits from economies of scope and synergy effects.

A complex banking organization can be a source of strength to its subsidiaries. Ashcraft (2008) compares different types of banking organizations and finds that banks affiliated with a multi-bank holding company (MBHC) are safer than stand-alone banks and banks belonging to a one-bank holding company. He attributes it to the increased availability of resources in other bank and non-bank subsidiaries, suggesting a risk-share function among the whole group. This is confirmed by Raykov and Silva-Buston (2020). They find that MBHC banks are more resilient to shocks than independent banks, and the market favors these banks after the crisis. In addition, Cetorelli and Goldberg (2012) document that the parent company could buffer the liquidity shock to those high-profitable affiliates through the internal capital market. Thus, complex organizational networks can help banking groups share risk through subsidiaries, and as portfolio theory suggests, revenue streams from different businesses or regions can diversify risk.

Another factor that benefits complex banks is the TBTF subsidy. Complex banks are typically considered TBTF institutions because their failure could result in significant and undesirable externalities. This status effectively provides complex banks with a free insurance policy against default. Moreover, the notion of TBTF status can benefit complex banks by gaining favor with bank creditors or investors, who are less incentive to charge a high price for their funds with this perception (Brewer and Jagtiani, 2013). Several studies have shown that large TBTF banks have an advantage in the deposit rate (Jacewitz and Pogach, 2018), credit rating (Ueda and Di Mauro, 2013), and equity capital (Gandhi and Lustig, 2015, Gandhi et al., 2020). However, TBTF also encourages banks to take on more risk as they are more likely to receive government support in times of distress (Afonso et al., 2014).

On the other hand, complexity may be associated with value loss and risk-increasing due to conflicts of interest and agency problems. The separation of ownership and management creates goal incongruence or interest conflicts between shareholders and managers (Jensen and

Meckling, 1976). In the context of bank complexity, the managers are more informative than the shareholders, and thereby, they may have stronger incentives to pursue their private interests at the cost of sacrificing bank value. These private interests include not only the consumption of perquisites or avoiding effort but also the action of empire-building, increasing managers' control, and reducing the probability of takeover (Hughes et al., 2003). Another agency cost arises from the headquarters-subsidiary relations (O'Donnell, 2000, Kostova et al., 2018, Filatotchev and Wright, 2011). Similar to human behavior, subsidiaries can also act in their self-interest, prioritizing the interests of the subsidiaries over those of the whole group[26] (Mudambi and Navarra, 2004). Based on the assumption of self-interest and bounded rationality, the behaviors of subsidies are shaped by cultural and institutional forces, which is a source of information asymmetry and thus generates interest conflicts (Kostova et al., 2018). Moreover, as banks expand into new business lines and locations, it is difficult and costly for the parent to monitor all subsidies effectively, resulting in moral hazard. Scharfstein and Stein (2000) argue that a multi-level agency structure can lead to divisional rent-seeking and inefficient investments. In addition, a broad of businesses would also intensify the conflicts of interest among different affiliates, such as banking and underwriting, trading and brokerage (Mehran and Stulz, 2007).

The opacity of complex banks can also contribute to risk-taking behavior. Bank complexity can be a source of opacity due to the uncertainty of publicly available information about banks (Jones et al., 2013) and the difficulties in identifying risk (Flood et al., 2020). Several studies have shown a positive relationship between opacity and bank risk-taking because opacity (Tran et al., 2022, Fosu et al., 2017, Moreno and Takalo, 2016). This is associated with increased financing costs for less transparent banks (Cao and Juelsrud, 2022) and reduced efficiency in financial markets (Blau et al., 2017).

The above analysis discusses possible channels through which complexity affects bank value or risk-taking. In previous literature, there has been limited exploration of the impact of complexity on bank valuation. This is because the concept of complexity is similar to diversification, especially at the business and geographical levels. In terms of bank diversification, it is still controversial whether banks that are diversified in their businesses or geography are more valued in the stock market. Among the studies related to business diversification, Laeven and Levine (2007) document that in the United States, the market value

[26] Kostova et al. (2018) argue that subsidiaries may exaggerate their performance to headquarters, misrepresent the unit's capabilities in order to gain access to resources, or violate the company's code of conduct in order to gain access to the unit's benefits, even if these actions are detrimental to the organization as a whole.

of banks engaged in various businesses is lower than that of banks specialized in individual activities. Similarly, Guerry and Wallmeier (2017) find a significant diversification discount before the 2008 financial crisis with a large cross-country sample. In contrast, studies in other countries show a positive relationship between bank diversification and market performance (Sawada, 2013, Baele et al., 2007b, Elsas et al., 2010). As for geographic diversification, Deng and Elyasiani (2008) find that it is value-enhancing. Yildirim and Efthyvoulou (2018) suggest a positive effect on bank value when banks in emerging markets expand into counties in the same region, while it becomes negative in the case of global diversification. Based on the above analysis, I formulate the first hypothesis on bank value:

Hypothesis 1. More complex banks have a higher market value.

Considering that bank risk is a paramount concern for financial stability, more literature has shed light on the impact of complexity on risk. Correa and Goldberg (2022) comprehensively analyze the relationship between complexity and different types of bank risk in the U.S. banking market. Their findings indicate that increases in organizational, business, and geographic complexity lower stock return volatility. Organizational and business complexity reduce bankruptcy risk, while geographic complexity mitigates liquidity risk. Additionally, all these forms of complexity exhibit positive correlations with systemic risk, suggesting that banks make trade-offs between different risks. In contrast, Martynova and Vogel (2022) find that bank risk positively correlates with complexity in all three dimensions in Germany. They also note German banks have become less complex, and the complexity-risk nexus has decreased in recent years in response to tighter regulations. Other studies show a varying effect among different dimensions of bank complexity. Argimón and Rodríguez-Moreno (2022) reveal that in Spanish banks, the higher the organizational and operational complexity, the higher the risk of insolvency, whereas an increase in geographical complexity reduces bank risk. Similarly, Marinelli et al. (2022) show that Italian banks with higher geographic complexity tend to adopt more prudent lending policies towards riskier borrowers and are therefore, more flexible in controlling the risk exposure of their loan portfolios. However, banks with diversified businesses have to take on more risk in a competitive market due to the cross-selling strategy. Furthermore, according to Aldasoro et al. (2022), geographic complexity plays a dual role by buffering the local economic shocks while softening regulatory constraints and encouraging risk-taking, thus exhibiting two opposite effects on risk. Given the intricate

mechanism underlying how complexity influences banks' risk-taking, I formulate the following two hypotheses:

Hypothesis 2a. Bank complexity increases the risk profile of banks.

Hypothesis 2b. Bank complexity decreases the risk profile of banks.

4.2.3 Complexity, bank value, and risk: the moderating effect of governance

It is argued that the effects of complexity are conditional on the governance (Correa and Goldberg, 2022, Argimón and Rodríguez-Moreno, 2022). Intuitively, banks with stronger corporate governance structures can more effectively monitor the managers, balance stakeholder interests, and enhance operational transparency, which helps reduce agency costs associated with complexity. This is related to the strand of literature that addressed the impact of governance on bank performance (see the litereture review in Hagendorff, 2014).

Several practices have been employed to mitigate the conflicts between shareholders and managers. As Jensen and Meckling (1976) point out, shareholders are more willing to take risks to make profits than external creditors and managers because they hold residual claims on the firm's assets, whereas creditors and managers with fixed compensation do not benefit directly from the wealth gains that come with high risk. Especially, in the context of the banking industry, shareholders prefer more aggressive management due to the highly leveraged business model (Hagendorff, 2014). Executive compensation policies are a common method to align the interests of managers with those of the stockholders, which encourages managers to adopt risky projects. This argument is supported by the empirical studies that show a positive link between compensation and bank stability (DeYoung et al., 2013, Bai and Elyasiani, 2013). However, dissenters argue that even if managers are likely to receive higher compensation, they may not necessarily become risk-seeking because their personal wealth is less diversified (Guay, 1999), and in-the-money options can make managers averse to increased firm risk (Parrino et al., 2005).

The monitoring and advising function of the board is another factor that may influence the complexity effect. A large body of literature has addressed the effects of board size and outside directors. A popular view in the literature is that smaller boards and more outside directors provide a more effective monitoring (Harris and Raviv, 2008, Boone et al., 2007, Coles et al., 2008, Dalton et al., 1999). With the increased size of the board, the monitoring is less effective due to the free-rider problems and longer decision-making time (Jensen, 1993). Unlike inside

directors, outside directors have no direct interest conflicts with the company and are, therefore, more independent in monitoring managers (Raheja, 2005). Weisbach (1988) shows that CEOs are more likely to resign after a poor performance in an outsider-controlled board, suggesting outsiders are active in monitoring.

As for the advisory role, the larger the board, the greater the advantage in expertise and resource providers (Dalton et al., 1999). In particular, Coles et al. (2008) and Adams and Mehran (2012) highlight the importance of larger boards in complex firms as they find that firm performance is positively linked with board size. Adams and Mehran (2012) state that having more directors from subsidiaries is necessary, as it facilitates coordination and monitoring. Furthermore, several studies have shown that appointing outsider directors can receive more valuable advice. They can be the CEO of another company (Fich, 2005) or a representative of a major customer (Kim et al., 2023), who can provide different perspectives or enhance the supplier–customer relationship and reduce information asymmetry. However, lacking firm-specific knowledge and information may offset the benefits of having an outsider director. Some studies indicate that outsiders do not have as easy access to information as insiders and tend to rely more on managers' information (Fahlenbrach et al., 2017, Adams and Ferreira, 2007). It can be anticipated that outsiders may look "naive" in a complex banking organization.

Suppose governance arrangements related to executive compensation and board composition impact bank performance. In that case, their effects should be more pronounced for complex banks, as stronger governance will likely be more valuable for such institutions. This leads to the following hypothesis:

Hypothesis 3. Banks with better governance can mitigate the adverse effects of complexity.

4.3. Data and methodology

4.3.1 Data

This study examines the relationship between bank complexity and market performance in the Japanese banking industry. The banking sample includes traditional commercial banks, trust banks, and banking holding companies. Most new forms banks, except for SBI Shinsei Bank and Aozora Bank[27], are excluded from the sample as their ultimate parent companies are

[27] SBI Shinsei Bank and Aozora Bank used to be Long-Term Credit Banks and transformed into normal commercial banks in 2004 and 2006, respectively. The observations before their transmission are excluded from the sample.

not banking-related. For example, the ultimate parent of Japan Post Bank is Japan Post Holdings Co., which primarily operates in the postal service business. While many large conglomerates in non-banking industries are permitted to establish bank subsidiaries, their core business remains unchanged, and entering the banking sector is seen as a diversification strategy. Consequently, when examining the impact of bank complexity on the entire group, the original businesses of these conglomerates may introduce additional bias. In addition, bank observations are not included once they become a subsidiary of a banking holding company to prevent duplication issues.

The sample is unbalanced panel data consisting of 1845 bank-year observations for 114 banks or BHCs over 2000-2020. The starting year for this analysis is 2000, as the deregulation allowing the establishment of BHCs in Japan was passed in 1997, and banks began transitioning into BHCs in 2000. This 21-year-long period is sufficient to reflect the trend of bank complexity patterns.

As bank complexity is measured based on their subsidiaries, I obtain the subsidiary's information from *NEEDS Corporate Basic Data*, provided by Nikkei Media Marketing, Inc., a famous information provider in Japan. This data contains information on the number of consolidated subsidiaries (over 50% of shares) and related companies (20%-50% of shares) for each listed company annually, as well as a specific list of each type of company, including its name, location, capital, business content, and percentage of voting rights. This information enables us to identify the ultimate patient of each bank (if it has one) and its subsidiaries or other companies under the same group. However, not all subsidiary information is listed, especially for large banking groups. This may not affect our results because it only accounts for 6% of the whole sample, and the fixed effects can absorb parts of missing information[28]. The accounting and stock market data are collected from the *Nikkei NEEDS Financial Quest database*. The yield for Japanese Government Bonds (JGBs) with different maturities is obtained from a historical database provided by the Japanese Ministry of Finance. Finally, I manually collect the governance data for each bank or BHC from their annual reports.

I process the collected data in these ways to make the regression results more reliable. First, I use consolidated accounting data to measure variables, and unconsolidated data is also accepted if the bank has no subsidiary. Then, I filter out banks with less than 3-year

[28] To further address this issue, I use a dummy variable to control for the possible effects of missing information, and the results remain unchanged.

observations and drop bank-year observations if there are fewer than 115 trading days in one year (about half of a year's trading days).

4.3.2 Empirical specification

To test the hypothesis 1 and 2, which investigate the impact of bank complexity on performance, I estimate the following equation:

$$Performance_{i,t} = \alpha + \beta Complexity_{i,t-1} + \gamma Control_{i,t-1} + \mu_i + \theta_t + \epsilon_{i,t} \quad (1)$$

where *i* is the bank identifier, and *t* denotes time. $Performance_{i,t}$ is a measure of bank market value and risk. $Complexity_{i,t-1}$ is a proxy for bank complexity, measured from organizational, business, and geographic dimensions. I use lagged terms of the independent variables to address the simultaneity. $Control_{i,t-1}$ is a vector of control variables that measures bank characteristics that may affect market value or risk. μi and θt denote individual and year-fixed effects.

As governance may affect the complexity effect, I first estimate the effect of governance on bank performance with a similar specification that includes the governance variable but excludes the complexity variable. Then, an interaction term between complexity and governance is introduced to test the moderating effects of governance. The specification is set as:

$$Performance_{i,t} = \alpha + \beta Complexity_{i,t-1} + \gamma Governance_{i,t-1} + \delta Complexity_{i,t-1} \times Governance_{i,t-1} + \eta Control_{i,t-1} + \mu_i + \theta_t + \epsilon_{i,t} \quad (2)$$

where $Governance_{i,t-1}$ represents the governance characters for bank *i* in time *t*. I measure bank governance from management compensation and board composition. The coefficient δ captures the moderating effect of governance. Specifically, if δ is significantly positive (negative), it suggests that governance can enhance (mitigate) the complexity effect, thereby confirming hypothesis 3.

4.3.3 Variables

In this section, I describe the main variables used in the empirical model. The specific definition and calculation of variables are shown in Table 4-1.

(1) bank performance

Generally, bank performance is typically evaluated based on its accounting or market performance. This paper prefers to focus on how the stock market values bank complexity because the stock price contains more information about profitability, growth opportunity, and investor attitude, not limited to a single aspect of performance (Lubatkin and Shrieves, 1986). In addition, accounting profitability tends to reflect short-term performance and can be more susceptible to manipulation and distortion due to complex accounting operations (Chakravarthy, 1986). Last but not least, using stock price data allows us to generate more risk measures, which helps understand banks' risk-taking behaviors. However, market-based measures also suffer from several problems, such as market inefficiency and limited samples. Overall, as discussed in Gentry and Shen (2010) , there is no consensus on which metric is better as they represent different logic, while sometimes they are related and, therefore, can be treated equivalently.

I use Tobin's Q as a proxy for market-based performance. Tobin's Q is calculated as:

$$Tobin's\ Q = \frac{market\ value\ of\ equity + book\ value\ of\ debt}{book\ value\ of\ equity + \ book\ value\ of\ debt} \tag{3}$$

I use the average market value of equity in March for each year in the calculation because the fiscal year of Japanese banks ends in March.

Tobin's Q is commonly used in previous banking studies (Baele et al., 2007b, Sawada, 2013, Elyasiani and Zhang, 2015, Laeven and Levine, 2009). It measures the difference between a bank's market value and its assets' replacement cost. A higher Tobin's Q, typically exceeding 1, indicates that the market places a higher value on the bank. Investors are willing to pay a premium for the bank rather than its replacement cost due to the expectation of long-term returns. Therefore, Tobin's Q is employed to gauge a bank's franchise value or long-term performance.

In addition to stock performance, this paper also focuses on bank risk-taking behaviors. I compute bank risk measures: (i) total risk, the standard deviation of daily stock returns over the fiscal year of Japanese banks (April to March of next year); (ii) systematic risk. It is proxied by the beta of a market model. In order to get the year-varying beta, I estimate the following two-index market model for each bank and year as suggested by Sun and Liu (2014) and Pathan (2009) :

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \gamma_i Interest_t + \epsilon_{i,t} \tag{4}$$

where $R_{i,t}$ is the logarithmic return of bank i in day t, and $R_{m,t}$ is the return on the Tokyo Stock Exchange Price Index (TOPIX). As some studies argue that the single-index model should introduce other risk factors that affect bank stock returns (Baele et al., 2007a), such as interest rate shocks, unexpected inflation shocks, or exchange risk shocks, I include the interest rate risk to regress a two-index market model since bank stock return is highly correlated with interest rate changes (Flannery and James, 1984). $Interest_t$ is the yield on the one-year Japanese Government Bond rate[29]. The coefficient of $R_{m,t}$, beta, measures the systematic risk of a bank. I also estimate the idiosyncratic risk, the standard deviation of the residuals of estimated market models, and employ it as an extra proxy for bank risk in the robustness. (iii) insolvency risk. Z-score is widely used to measure a bank's insolvency risk. According to Laeven and Levine (2009), the Z-score is calculated as

$$Zscore = \frac{ROA + CAR}{\sigma_{ROA}} \tag{5}$$

where CAR is the equity to assets ratio (E/A) and σ_{ROA} is the standard deviation of ROA, calculated based on a past three-year rolling time window. Z-score measures the possibility of insolvency, that is, the losses surmount equity ($E< -\pi$). A higher Z-score indicates a lower possibility of insolvency, and thus, the bank is more stable. Furthermore, I take the natural logarithm of the Z-score, as the Z-score has a highly skewed distribution.

(2) bank complexity

As mentioned above, there are several metrics of bank complexity. I follow the method proposed by Cetorelli and Goldberg (2014) to measure complexity in three dimensions: organizational, business, and geographic. The construction of complexity indicators is based on the information about the business content and location of the subsidiaries.

Organizational complexity reflects how the organization is structured through separate legal entities. Banks, especially BHCs, need multiple subsidiaries to operate bank and non-bank businesses, possibly due to regulatory constraints, specialization, tax considerations, or other reasons. There is no clear answer as to which structure is optimal for a bank, and an efficient group will adjust its structure to achieve the optimal state. Therefore, the current structure is

[29] Sun and Liu (2014) and Pathan (2009) use the yield on the three-month Treasury-bill rate to measure the interest rate shocks, while similar yield data is not available in Japan. Therefore, I use the yield on the shortest government bonds as an alternative indicator. Furthermore, I also use the yield on a long-term government bond, such as 10-year, and the results remain unchanged.

assumed to be a rational choice for this group. Therefore, I use the number of affiliates, including the ultimate parent company[30], to measure organizational complexity. An increase in the number of subsidiaries makes the group more organizationally complex as it cannot be aligned with the current structure, and the group needs to pay for this adjustment, such as new management or excess transaction costs. However, it's worth noting that this indicator may be somewhat arbitrary since it only considers the number of subsidiaries while overlooking other connections, such as cross-holdings or pyramidal structures. Moreover, due to the extremely large number of independent entities in a few banking groups, I use the logarithm of the number to mitigate the possible bias of scale.

Business complexity refers to the range of businesses in which a bank or BHC is engaged. In general, the more business a bank engages in, the more complex it is. Following Correa and Goldberg (2022), I measure business complexity using (i) the number of business scopes spanned by subsidiaries. (ii) the number of banks[31]. Compared with independent banks, groups with more bank subsidiaries are considered more complex because the risk is easier to infect within the group in a crisis. (iii) the number of non-financial subsidiaries. As banks are supposed to specialize in financial businesses, engaging in other non-financial businesses would increase their complexity. (iv) a Herfindahl-Hirschman Index (HHI) for industries distribution of all subsidiaries. A higher HHI indicates a more decentralized distribution of subsidiaries across industries and, therefore a more diversified and complex group.

A key point in constructing the business complexity variables is to identify the industry to which the subsidiary belongs. Unfortunately, the industry information is not available in the subsidiary data. Therefore, I refer to the Japan Standard Industrial Classification (Reversion 13) published by the Japanese Ministry of Internal Affairs and Communications and categorize the subsidiaries based on the keywords in the company names and business contents. The specific procedures for classification are shown in Appendix 1.

Geographic complexity focuses on the multinational activities of banks and is measured based on the location of subsidiaries. Banks with subsidiaries in different countries are considered more complex in geography. Thus, the geographic complexity is proxied by (i) a dummy variable for holding subsidiaries abroad. It equals 1 if a bank has a foreign subsidiary this year.

[30] One reason for including the ultimate parent company is that some banks in Japan have no subsidiaries, rendering it meaningless to take the logarithm of the number of subsidiaries. I also exclude the banks with no subsidiaries and use the number of subsidiaries (in natural logarithms) as an alternative measure, and the results are similar to the baseline regression.
[31] For banks with no parent company, the number of subsidiaries is calculated as the true number of subsidiaries plus one (the bank itself) in order to make the measure the same as for BHCs.

(ii) the number of counties spanned by subsidiaries. (iii) the number of foreign subsidiaries. (iv) a similar HHI for location distribution of all subsidiaries.

Since several variables are employed to measure the business and geographic complexity, the independent variables are too numerous for comprehensive analysis and reporting. Therefore, in line with Buch and Goldberg (2022), I use principal components analysis (PCA) to reduce the dimensionality of the dataset. This method generates several principal components encapsulating most information through the orthogonal linear transformation. Table 4-2 shows the results of PCA, including the eigenvectors of the first principal components and the proportion of explained variance. For business complexity, I only use the first principle component even though the eigenvalue of the second principle component surpasses 1. This still makes sense because the first principal component contains the most information from the original variables, and, more importantly, the correlation coefficients between the first principal component and the original variables are all positive but not for the second principal component.

(3) governance

Bank governance is measured based on the board's composition in this paper. This is because the board plays an important role in monitoring and advising. Notably, a distinctive feature of the Japanese banking sector is the comparatively lower proportion of independent board directors compared to their counterparts in the United States,. In the Japanese context, insider directors are usually top executives, and the board tends to play a more active role in business decisions, especially in the past. Therefore, the indicators about the board can be used to measure how governance affects complexity effects.

The first variable of governance is the shareholding of the board, which is calculated as the ratio of shares held by the board to outstanding shares. This is a proxy for executive compensation, as directors can benefit from an increase in stock price. With a higher stake in bank stocks, directors are expected to align more closely with shareholders, potentially leading to a willingness to undertake greater risks for profit. The second variable is the board size, that is, the number of directors. A large board in a complex banking organization can offer more valuable advice, and it seems to be necessary to have more directors from the bank's subsidiaries to mitigate agency costs in headquarters-subsidiary relationships. On the other hand, a large board may also face inefficiencies due to the free-rider problem and extended decision-making times. The third variable is the share of independent directors. A higher share of independent directors is expected to reflect a stronger function in monitoring and advising. However, it is important to note that a higher share of inside directors does not necessarily

indicate weaker governance in Japanese firms, as the emphasis on the operational decision-making function of the board is more prominent. Under this context, outsider directors are at an informational disadvantage and less specialized, which indicates a trade-off between the board's different functions when the board's size is fixed.

(4) control variables

I control several bank-level characters that are found to affect bank performance in the regression.

It includes bank size, equity ratio, loan-deposit ratio, assets growth rate, funding costs, overhead ratio, non-performing loan, ROA, and dummy variables for bank merge and missing information.

The equity ratio reflects the capital structure of banks. Banks with high equity ratios are considered more stable, as equity serves as a cushion against losses, which may be more valued by the markets. However, maintaining a high equity ratio can also be costly, as it can limit bank expansion, and banks are encouraged to take on riskier portfolios when insolvency risk is low. The loan-deposit ratio reflects how banks utilize deposits between lending and other businesses. This indicator is highly valued in the Japanese market as it is also a proxy for business prosperity. A high loan-deposit rate means that more deposits are being used for lending, credit is expanding, and the economy is booming. Asset growth rate measures a bank's growth, and rapid expansion of a bank's assets can affect its share price. Funding costs and overhead ratio measure cost efficiency, and more cost-efficient banks are expected to perform better in the stock market. Non-performing loans (NPLs) capture the quality of a bank's loans, with higher NPL ratios indicating higher expected future losses. ROA is a common indicator of bank profitability and will be reflected in the stock price. I use a dummy variable for bank mergers to control the possible effects of a merger between two Japanese banks. If a bank merges with another bank that does not belong to one group in year T, the dummy variable equals 1 in this year. Unlike other independent variables, the merge dummy does not take a lagged form in regression because it is assumed that the market will react quickly to this merger. I also consider the long-term effect of bank mergers by setting dummy variables to 1 after the year of the merger. The results show no significant difference between the two methods. Finally, I use year-fixed effects to control the macro-environmental characteristics.

4.3.4 Summary statistics

To offer additional insights into the sample, Table 4-3 presents descriptive statistics of the regression variables. All continuous accounting variables are winsorized at the 1st and 99th percentiles to mitigate the impact of outliers.

First, I discuss the complexity pattern of Japanese banks. The mean value of organizational complexity, quantified by the number of separate legal entities in a bank group, is 16, which seems to be a large number. However, the standard deviation is much larger than the mean, suggesting a significant variation across banks. This is confirmed by the minimums and the median, where at least one bank has no subsidiaries, and the median is considerably smaller than the sample mean. This may be because a few banking groups control many subsidiaries, such as Japan's four city banking groups. In terms of business complexity, a noteworthy observation is that most Japanese banks are involved in diverse financial activities, as evidenced by the fact that the mean and median are both at 5, close to the maximum. Another point relates to non-financial subsidiaries, with over half of the banks have at least three subsidiaries operating outside the financial sector, including industries such as information and software, and real estate. The last variable serving as a proxy for business complexity is the business HHI, which has a mean value of 0.716. A higher value of this variable indicates a more decentralized distribution of subsidiaries across industries. The statistics on the business complexity variable suggest that Japanese banks are well organized in their business despite the limited number of subsidiaries. When it comes to geographic complexity, I find that most Japanese banks have no foreign subsidiaries and only a few bank groups engage in global business expansion. This suggests that Japanese banks are more focused on the domestic market and have less incentive to expand overseas than banks in the United States (Correa and Goldberg, 2022) or Germany (Martynova and Vogel, 2022).

Next, I provide some facts about the evolution of bank complexity and governance in Japan. Figure 4-1 and Figure 4-2 show the mean values of complexity and governance variables for banks of different sizes from 2000 to 2020, shedding light on the dynamic changes in complexity and governance patterns. The solid line represents the mean of the entire sample, while the dashed (dash and dot) line represents the mean values for large (small) banks, defined as those with assets above (below) the average assets in each year. In Panel (a) concerning organizational complexity, there is an upward trend until 2009, followed by a period of stability before a brief fluctuation in 2018. Notably, the trends for small and large banks diverge, with the average number of subsidiaries declining since 2000 for small banks, while large banks exhibit a similar trend to the sample mean. The difference is also significant in business

complexity, shown in Panel (b). The number of business scopes has decreased rapidly since 2000 for small banks, whereas large banks are actively expanding their business. For business HHI, both small and large banks initially displayed a trend towards greater industry diversification before 2009, after which small banks shifted to focus on a select few industries. A parallel trend for both banks is the decline in non-financial subsidiaries, indicating a strategic withdrawal from the non-financial industry since 2000. In Panel (c) on geographic complexity, small and large banks exhibit a similar trend, with most banks expanding their business abroad before 2009 and subsequently rapidly retracting from foreign markets. Across all measures, the current complexity levels have not returned to those observed in 2009, suggesting a cautious attitude towards overseas expansion. Notably, almost all complexity measures experienced fluctuations after the 2008 financial crisis, indicating that this crisis significantly impacted banks' complexity strategy.

Regarding governance measures, I find no significant difference between small and large banks. Particularly in independent share, the trends almost overlap for most of the analyzed period. Notably, boards in small banks tend to hold more bank stocks than those in large banks. This observation may be attributed to the presence of family members, who founded the bank, still serving on the board, a phenomenon more prevalent in small banks. Another difference is the rapid increase in board shareholding in small banks from 2015 to 2020, while the trend in large banks leans towards a decrease. Additionally, I find that Japanese banks have been reducing their board size in recent years. Panel (b) illustrates two waves of board size reduction—one before 2004 and another after 2014. Furthermore, there is a clear upward trend in the share of independent directors, as depicted in Panel (c). Owing to regulatory requirements, the mean value has quadrupled in 2020 compared to 2000. This also implies a shift in board composition, with more insiders being removed from the board against the backdrop of a decline in board size.

Lastly, I present the correlations between independent and control variables in Table 4-4. The complexity measures exhibit a positive correlation with bank size, with a correlation coefficient exceeding 0.7. This explains why some studies utilize bank size as a proxy for complexity. However, excluding bank size from the model to address concerns about collinearity may not be advisable. Multicollinearity can inflate variance in results, potentially yielding p-values below a critical threshold. If the coefficient remains significant despite multicollinearity, it suggests that the true variance should be smaller, thereby enhancing the reliability of the results. Moreover, I employ 2SLS regression analysis in most regressions, which can alleviate

multicollinearity as the predicted complexity variables in the second stage may be less correlated with bank size.

4.4. Empirical results

4.4.1 Complexity and bank performance

First, I report the regression results of Equation (1), where bank performance is regressed on three dimensions of complexity variables. For business and geographic complexity, the results of the principal components of complexity variables are presented.

Table 4-5 presents regression results on bank complexity and Tobin's Q. In Columns 1, 4, and 7, I show the baseline results from the fixed effects model. The coefficient of business complexity is positively linked with Tobin's Q at the 5% significant level, while the coefficients of other complexity measures are similarly positive but not significant. These results indicate that banks can become more complex in business to increase their market value. On the other hand, banks with more subsidiaries or expanding their business abroad are not necessarily valued by the market.

However, these results may be biased due to the endogeneity of complexity variables. It is commonly assumed that complexity influences bank performance, but it is crucial to consider that bank performance can also affect a bank's organizational structure. For instance, banks may be motivated to adopt a more complex structure if they can benefit from the current structure. Even if complexity correlates with increased risks, managers may take on more risk to offset additional costs. To address the reverse causality between performance and bank complexity, I conduct the instrumental variables analysis using a 2SLS model and system generalized method of moments (SYS-GMM) estimation proposed by Arellano and Bover (1995) and Blundell and Bond (1998). In the IV regressions, two instruments are employed. The first instrument is the complexity level of competitors, calculated as the average organizational and business (geographic) complexity of the 20 (4)[32] banks with the nearest bank size each year. Competitors are identified as the 10 (2) banks smaller than the target bank and the 10 (2) banks larger than the target bank[33]. This is reasonable because banks tend to mimic the behavior of their competitors, and average complexity is not directly related to the

[32] I choose fewer competitors to measure geographic complexity because the correlation between IV and geographic complexity is not significant when more competitors are chosen.
[33] For banks with insufficient competitors, the calculation is based on all eligible banks. For example, in the case of the smallest bank, it is calculated as the average complexity of the 10 (2) banks larger than the target bank.

performance of the target bank. The second IV is the lag of independent variables, the two-year lag of the complexity variable. This method is also used in other bank performance studies, such as Elsas et al. (2010) and Demirgüç-Kunt and Huizinga (2010). In SYS-GMM estimation, to address the endogeneity arising from introducing the lagged dependent variable to the right-hand side, the first-differenced variables are used as instruments in the level equations, except for the lagged variables served as instruments in the difference equations. Furthermore, to prevent the utilization of an excessive number of instruments in estimation, I limit the lagged instruments for the dependent variable to 2 to 4 and for explanatory variables (excluding time-fixed effects) to 2 to 3, employing a collapsing technique.

The other columns in Table 4-5 show the results of the two methods. Column 4 suggests that the positive relationship between business complexity and market value remains unchanged when using IV regressions. On the other hand, when considering the dynamic of the dependent variable, geographic complexity is found to positively affect the market value, as shown in Column 9. The baseline results and additional checks partly support hypothesis 1. Not all forms of complexity are valued by the market, and banks can adopt business complex strategies to enhance their market value.

Table 4-6 shows the results for the nexus between bank risk and complexity, with Panels A, B, and C presenting the results for total risk, systematic risk, and insolvency risk, respectively. Similarly, I also report the results for the fixed effects model and two other methods. In panel A, there seems to be no correlation between bank complexity and total risk since the coefficients of complexity from the fixed effects model are insignificant. However, it becomes significant for business complexity after considering the endogeneity issue. Columns 5 and 6 show that the coefficients of business complexity are negatively significant at the 10% level, suggesting that business complex banks tend to have a lower volatility in their stock returns. In Column 3, although the coefficient is significant, the result is less robust as it does not hold in the IV regressions. Panel B shows the results for systematic risk, measured by the market beta. Only Columns 3 and 9 show a negative relation between organizational and geographic complexity and systematic risk. This indicates that banks with more domestic or foreign subsidiaries have lower systematic risk. In other words, the correlation between the market portfolio and the stock prices of these banks is relatively smaller. It is important to note that the signs estimated from the fixed effects model and IV regressions are strongly against this result. Even though they are not statistically significant, a positive correlation with systematic risk is anticipated. This can be attributed to including the lagged dependent variable as an explanatory variable, where the coefficients of other variables reflect the information not

included in the lagged dependent variable. Therefore, it can be explained as a negative effect on systematic risk if the lagged dependent variable is considered indispensable in the specification.

In Panel C, the results show a negative relationship between complexity and insolvency risk. In the fixed effects model, banks with a higher business complexity are found to have a lower z-score and are more likely to go bankrupt. Organizational and geographic complexity can also lead to a decrease in z-score but is not statistically significant. Moreover, the results of the two methods verify the negative effects on insolvency risk, as shown in Columns 3, 6, and 8. Similarly, Martynova and Vogel (2022) also find complex banks tend to have a higher insolvency risk in the German banking industry. Conversely, Buch and Goldberg (2022) suggest a decreasing bankruptcy risk for complex banks in America.

Overall, the above results on bank risk indicate two opposite complexity effects, and thus, hypotheses 2a and 2b are both partially supported. Specifically, business complexity is associated with a lower total risk, while organizational and geographic complexity can reduce banks' systematic risk but is less robust. On the other hand, all forms of complexity lead to higher insolvency risk. One plausible explanation for this difference is that complex banks take on more risk to pursue profits, and the market values actual profits more than potential risks. This implies that banks engage in trade-offs between various risks, as proposed by Buch and Goldberg (2022).

4.4.2 Governance, bank performance, and moderating effects

To test whether bank governance affects complexity effects in the Japanese banking industry, I initially regress performance on governance indicators to assess how governance affects bank performance. Table 4-7 reports the results for the shareholding and composition of the board from a fixed effects model. As noted by Adams and Mehran (2012), it is difficult to find appropriate IVs for governance variables since potential IVs may also be correlated with performance variables. Hence, despite certain tests suggesting the potential inadequacy of these IVs, I continue to employ the average governance of competitors and lagged independent variables as instruments. The results are shown in Table A4-2 and remain unchanged from the fixed effects model.

Columns 1 to 3 show the results when Tobin's Q is regressed. I can not find evidence that bank governance directly impacts bank value, as all coefficients are insignificant. This can be attributed to two opposite effects on governance or just the market not valuing the governance arrangement. Columns 4 to 9 show the results for risk measures. I find that board shareholding

is negatively corrected with bank risk, suggesting that the board tends to take on less risk when they hold more bank stock. This evidence strongly contradicts the “stay with shareholders” hypothesis that management will take more risk, as expected by the shareholders when receiving stock-based compensation. As for the board's composition, the results suggest that a larger board size can reduce bank risk, while banks are more risky with more independent directors. The former is consistent with another study about the board size effect among Japanese firms conducted by Nakano and Nguyen (2012). They also find that Japanese firms with a larger board exhibit lower performance volatility. This supports the hypothesis that larger boards may be more effective in monitoring in Japan, as more advice may be taken into account in decision-making, which contradicts the evidence of “small but effective boards” found in other countries. The latter suggests an unexpected but interesting negative impact of the independent directors. In general, outside directors are expected to be more independent in monitoring and advisory, thereby curbing excessive risk-taking by managers. However, these results suggest that the outside directors ratio is associated with a higher stock return volatility. This may be explained by the fact that outside directors are less valued in Japanese banks as the independent board share is much lower than in the United States. This makes the outsiders a minority in decision-making, potentially reducing their incentive to fulfill their duties effectively. Moreover, as outside directors are at an informational disadvantage but are indispensable due to regulations, additional outside directors may contribute less than experienced inside directors. Overall, the results in Table 4-7 suggest that a large board, fewer independent directors, and higher executive compensation can reduce bank risk-taking behaviors.

The second step is to consider the moderating effects of governance. Table 4-8 reports the results of equation (2), and the key interest is the coefficients of the interaction term between complexity and governance. Considering the endogeneity of complexity, I employ the previously mentioned IVs and the interaction term between IVs and governance variables to instrument complexity-related variables. I have not considered the endogeneity of governance because it seems to have little effect on bank performance, as discussed before, and the regressions become complex if the endogeneity of both variables is considered simultaneously.

Panel A shows a significant negative effect on bank market value from the interaction term between board size and three complexity measures. This indicates that complex banks with small boards are more valued by the market, or in other words, there is no need to increase the board size to obtain a market premium when banks become more complex. The market seems to expect that banks can deal with the complexity under the current board size, and an increase

in the number of directors is not economic. Adams and Mehran (2012) also study the interaction effects of complexity and board size. However, they do not find complexity has a significant impact on explaining the positive relationship between board size and bank market value. My results provide new evidence to explain why small boards are valuable in some markets, as they can still be effective in complex banks. Another finding is outside directors are not valuable in the expansion of business complexity. As indicated in Column 6, the share of independent directors negatively influences the effects of business complexity. This implies that increasing the number of outside directors in business complex banks would harm their market value. One plausible interpretation of this result is that highly complex banking organizations necessitate competent professional outside directors. Evidently, the market anticipates that the existing pool of outside directors in Japan lacks the required expertise and selection criteria, which hinders their effectiveness. As for the board shareholding, aligning managers' interests with shareholders in complex banks may positively affect bank value, but the influence is insignificant.

Panel B to D presents the results of the interaction term when risk is regressed as the dependent variable. Except for the coefficient on the interaction with board shareholding in Panel D, which is negative and significant at the 5% level, the coefficients on other interaction terms are insignificant. Although I find governance influences banks' risk-taking behavior, there are no significant differences among banks with different complex levels, especially in market-based risk measures. The results in Columns 1 and 4, Panel D indicate that the potential risk-taking incentive is stronger in complex banks, possibly because it is easier to impede monitoring within an intricate organizational structure. This also implies that the board may prioritize risks directly pertinent to them, such as the volatility of the stock they own, over potential long-term risks.

In sum, I find that the moderating effects of governance are more significant on bank market value. A small board and fewer outside directors in complex banks are more valuable. This implies that banks should consider controlling the number of boards and outside directors when implementing a strategy to increase complexity. On the other hand, governance has a limited impact on mitigating banks' risk-taking incentives in Japan. Conversely, an increase in board shareholding, which reduces overall bank risk, may lead to increased risk-taking if the bank has a complex structure. These findings reject Hypothesis 3, as better governance arrangements, associated with stronger monitoring, such as larger boards or more independent directors, do not seem to effectively mitigate the adverse effects of complexity.

4.4.3 Additional robustness test

(1) alternative measures for market value and risk, and more IVs

In the baseline regression, I employ Tobin's Q and two market-based risk measures to assess bank market value and risk. To provide a more comprehensive understanding of the impact of complexity on bank performance, I introduce two alternative measures. The first proxy is the market-to-book (M/B) ratio, derived from the ratio between the market value and book value of equity. A higher M/B ratio indicates that the bank is more valued by the market. The second proxy is idiosyncratic risk, defined as the residual risk after subtracting systematic risk from total risk. It is calculated as the standard deviation of the residuals in Equation (4). Moreover, although I use two IVs to address the endogeneity of complexity, the exogeneity of the lagged independent variable is debatable. However, it is difficult to find proper time-varying IVs for complexity, as IVs constructed from bank-level characters may not fully satisfy the exogeneity requirement. One solution is to "let the data speak for itself". Following the method proposed by Lewbel (2012), I use the heteroskedasticity-based instruments generated from the error structure of the first-stage IV regression. This method can generate IVs that do not depend on external variables but on their statistical properties, which is helpful when there are no suitable IVs. Nonetheless, a clear drawback of this method is that the generated IVs lack economic meaning and tend to be weak. A prudent approach is to find at least one plausible IV and incorporate the generated IVs as additional instruments. Therefore, I re-estimate the baseline model with alternative measures by employing the Lewbel (2012) method and using the average complexity level of competitors as one of the instruments.

Table 4-9 shows a positive relationship between business complexity and the M/B ratio, suggesting business complexity can add bank market value. In addition, banks with a high level of organizational and business complexity are found to have lower idiosyncratic risk. This is consistent with the baseline regression but suggests a more significant risk-decline effect for organizational complexity. However, the results may also be biased because the K-P Wald F statistic is small, implying the weak IV issue even though we have introduced an external IV.

As for the mitigating effects of governance shown in Table 4-10, the negative moderating effects of board size on bank value remain unchanged since the coefficients of the interaction terms are still significantly negative in Columns 2, 5, and 8, Panel A. Additionally, I find more evidence of idiosyncratic risk. The interaction term between board shareholding and organizational complexity is positive in Column 1, Panel B, suggesting that the risk-taking incentive of the board is stronger for banks that are more complex in organization. This is consistent with the findings on insolvency risk. Columns 5 and 8 indicate opposite moderating

effects of board size on bank risk. Smaller boards may be more effective in monitoring banks' risk-taking behaviors for business-complex banks, while the opposite is true in the case of geographic complexity.

(2) nonlinear relationship

In previous studies, researchers usually assume a linear relationship between bank complexity and performance. However, there could be a non-linear relationship, as the impacts of various channels may vary with increasing complexity. For instance, it is foreseeable that banks with a greater number of subsidiaries have to deal with conflicts of interest among their subsidiaries, whereas this might not be the primary concern for banks with fewer subsidiaries. Therefore, it is necessary to consider possible nonlinear relations in the context of complexity.

I introduce the quadratic terms of complexity variables in the baseline regression to capture the nonlinear relations, and the results are shown in Table 4-11. Similarly, to address the endogeneity concerns, I use the linear and quadratic terms of IVs to instrument the complexity variables. I find few significant nonlinear relationships between different complexity measures and performance. Column 1 indicates an inverted U relationship between organizational complexity and Tobin's Q. The turning point for this nonlinear relationship is 7.79[34], which approximately corresponds to the 52nd percentile. This implies that having more subsidiaries positively impacts a bank's market value when the number of bank subsidiaries is less than 7 (≈7.79 -1). However, it becomes a negative effect if banks have more than seven subsidiaries. This result implies that banks are not perceived favorably when they have excessive subsidiaries. In other words, the market seems to prefer banks that expand their business within limited group members. This preference may be related to the rising costs of maintaining numerous subsidiaries, such as conflicts of interest or increased monitoring costs. It's worth noting that this doesn't advocate for a universal cap on the number of subsidiaries for all banks but rather emphasizes the potential negative consequences of having too many subsidiaries. Banks should carefully evaluate whether it is necessary to increase the number of subsidiaries, consider expanding through existing subsidiaries, or contemplate merging some subsidiaries with similar functions. Columns 3 and 8 also show possible nonlinear relations but are less significant. Overall, nonlinear relationships are not significant for most complexity variables, and thus, the assumption of linearity in the baseline regressions still makes sense.

[34] The turning point is calculated as – ½ * Cofficient (organational) / Cofficient (suqaire of organational). Subsequently, the outcome is transformed using an exponential function to get the final result.

4.5. Further analysis

4.5.1 Channels analysis

In the above analysis, bank complexity is found to affect bank performance, especially from the perspective of business complexity. In this section, I try to discuss several channels that may explain why complexity improves performance.

(1) diversification benefits channel

One motivation for banks to acquire other firms or expand their business in the domestic or foreign markets is to achieve diversification benefits. Bank diversification refers to engaging more in non-traditional lending business. Some studies have shown that bank diversification has a positive impact on bank performance (Baele et al., 2007a, Sawada, 2013). Sawada (2013) examines the relationship between bank diversification and market-based performance in Japan and finds that diversification can enhance market value and reduce bank risk. If Japanese banks adopt a strategy of complexity to become more diversified, it is anticipated that there will be a positive relationship between complexity and diversification.

To capture the possible linkage, I employ the non-interest income ratio as a proxy for bank diversification, which is widely used in diversification-related studies. The non-interest income ratio is defined as 1 – interest income/operation income. I run similar 2SLS regressions with the IVs for endogeneity complexity variables proxied by lagged complexity variables and the average complexity level of competitors[35]. The results are presented in Columns 1 to 3, Table 4-12, where significantly positive relations are found between the non-interest income ratio and three forms of bank complexity. This result verifies the idea that banks with higher levels of complexity are more diversified in their income source. This is not surprising, at least for business complexity, since the expansion to non-banking industries naturally results in higher non-interest income. However, if banks want to expand their lending business through subsidiaries, the increase in organizational and geographic complexity is not necessarily positively correlated with the non-interest income ratio. The positive correlation with organizational and geographic complexity implies that banks acquire or establish new subsidiaries in the domestic or foreign market primarily to engage in non-interest business. This is consistent with the fact that the average non-interest income ratio has risen over the past two decades, and more non-financial target M&A transactions are conducted in the Japanese banking industry.

[35] In the following regressions, the competitors are redefined as 8 banks with the nearest bank size each year in calculating the average organizational and business complexity, because the old IVs are invalid in the overidentification tests.

As complexity is positively linked with diversification in Japan, similar effects on performance are anticipated, as shown in Sawada (2013). Our findings indicate a positive impact of business complexity on Tobin's Q and a reduction in total risk, which provides additional evidence for the diversification benefits found in Japan.

(2) funding costs channel

As banks become more complex, they are more likely to be considered TBTF institutions since the bankruptcy of these banks would affect financial stability. Therefore, complexity is also a criterion for identifying G-SIFS. As discussed earlier, being recognized as a TBTF institution gives complex banks an advantage in terms of funding costs, which could improve their profitability and be reflected in their market value. Thus, I expect a positive relationship between bank complexity and funding costs.

In the baseline regression, I find that higher funding costs are associated with lower Tobin's Q and higher market risk, which is consistent with the idea that banks with lower funding costs are more valuable and have less incentive to take on more risk to compensate for their funding costs than their competitors. To estimate the correlation between complexity and funding costs, I employ the funding costs calculated by the ratio of interest expense to average deposits, as the dependent variables to be regressed on bank complexity. Columns 4 to 5, Table 4-12 confirm this positive relation between organizational and business complexity and funding costs. The coefficients of these two complexity variables are negatively significant at the 1% level, suggesting that complex banks in organizations and businesses do have lower fund costs. According to the data published by the Japanese Bankers Association, the total costs on deposits and bonds of city banks are lower than that of the regional bank, and the second regional banks have the highest costs. My results can partially explain this fact as city banks are more complex than other banks, enabling them an advantage in funding costs. However, I find that geographic complexity has little effect on funding costs from Column 6. This implies that expanding business abroad cannot help bank groups effectively reduce their funding costs. Since domestic depositors pay less attention to banks' overseas operations, they may not accept a discount on deposit rates. Moreover, Japan has been one of the countries that have been most active in implementing a zero-interest rate policy over the past two decades, making it the region with the relatively lowest cost of funding for banks in the world.

(3) opacity channel

Several studies have shown that bank opacity encourages risk-taking behaviors (Tran et al., 2022, Fosu et al., 2017, Moreno and Takalo, 2016). As noted by Zheng (2020), bank opacity refers to a lack of informativeness in bank financial disclosure, making it difficult for outsiders to assess the true quality of bank assets. According to this definition, opacity can arise from incomplete financial disclosure and difficulty in comprehending the information. This issue is exacerbated for banks with a large number of subsidiaries operating in diverse industries or regions. First, the consolidation of financial reports becomes challenging due to complex transactions that differ from banking activities or domestic regulations Furthermore, disclosing detailed information about these subsidiaries, including income and asset details, is often impractical, at least in Japan. This lack of transparency hinders outsiders from gaining a comprehensive understanding of the banks' operations. Second, even when banks make efforts to provide more detailed disclosures, the intricate nature of a complex banking group introduces barriers for outsiders to grasp the true meaning behind the disclosed information since more factors and effects need to be considered. Therefore, bank complexity may lead to a higher level of opacity.

Following Cao and Juelsrud (2022), I use the market-based opacity measures as they reflect more information about the market participants' perceptions. The indicator is the ratio of "available-for-sale (AFS) securities[36]" to total assets, and a higher proportion signifies lower opacity for the bank. AFS securities are considered transparent assets since they are market-to-market, and the gains and losses can be reflected immediately in their equity value. Columns 7 to 9, Table 4-12 report the results for regressing opacity on bank complexity. It exhibits a negative correlation with business complexity but a positive correlation with geographic complexity. This implies that business complexity contributes to higher bank opacity, while geographic complexity leads to a reduction in bank opacity. It is not surprising to see a positive relation between geographic complexity and opacity, as banks are required to disclose more information in accordance with local regulations, potentially enhancing their transparency. It is also important to note that the opacity channel could explain the risk-taking incentives in insolvency risk shown in Panel C, Table 4-6, while not for the risk-decline effects in Panel A, Table 4-6. This may imply that opacity is not the main channel that contributes most to the net effects.

[36] In the balance sheet of Japanese banks, AFS securities are defined as trading securities or trading account assets.

4.5.2 Does bank size matter?

In Figure 1, a notable divergence in the evolution of bank complexity is evident between small and large banks. This raises a concern regarding whether the effects of complexity vary across banks of different sizes. I anticipate that small banks may experience fewer benefits but face higher risks when implementing a complexity strategy since they are disadvantaged in competing for market attention, such as Too Big to Fail (TBTF) subsidy, and are more vulnerable when confronted with risks. To address this concern, I re-estimate the baseline regression by segmenting the sample into two groups: small and large banks. Specifically, banks with total assets below the annual average are categorized as small banks. However, subsample analysis may introduce sample selection bias to the estimations. To mitigate this, I use the same IVs in the baseline regressions and employ 2SLS regression analysis to handle endogeneity. The results for the complexity effects on different-sized banks are presented in Panel A and Panel B of Table 4-13, respectively.

Table 4-13 reveals that a complexity strategy may not be a good choice for small banks, consistent with my expectations. In Column 3, Panel A, a negative impact of geographic complexity on bank value is observed for small banks, indicating that expanding abroad may detrimentally affect the market value of smaller institutions. Concerning bank risk, an increase in complexity is found to elevate the risk profile of small banks. Columns 4, 6, and 9 indicate that organizational and geographic complexity contribute to increased risks for small banks. On the other hand, in Panel B, business complexity exhibits a more pronounced positive impact on market value for large banks, albeit at the cost of increased risk. Columns 5 and 8, Panel B, suggest a positive effect on total risk and systematic risk when large banks enhance their business complexity. Moreover, Column 12 indicates that higher insolvency risk associated with geographic complexity is more significant for large banks. Overall, these findings highlight the differential impact of complexity on small and large banks. It implies that small banks may benefit from maintaining a lower level of complexity, especially being cautious when expanding abroad, as the market appears less favorable to such international expansion. For large banks, while increasing business complexity can enhance their value, careful attention should be paid to the concomitant risk-increasing effects.

Furthermore, I consider the possible difference in governance effects between small and large banks. In Table 4-14, I find most results in baseline regressions remain unchanged for both small and large banks, suggesting that bank size may not have a significant impact on governance effects. Still, there are some interesting differences between banks of different sizes. For example, the proportion of independent directors has a negative impact on the market value

of small banks, suggesting that the market does not value small banks having more independent directors. In the case of large banks, larger boards and a lower proportion of independent directors are more likely to be associated with enhanced monitoring of risk-taking behavior.

4.6. Conclusion

This paper discusses the recently hot topic of bank complexity and investigates its correlation with bank performance within the Japanese banking industry. Moreover, it explores the impact of governance on bank performance, assessing whether improved governance structures can mitigate the potential negative effects of complexity. Finally, it tests several channels that can explain the impact of complexity on bank performance and considers the heterogeneity between small and large banks on complexity and governance effects.

The empirical results reveal that not all forms of complexity can increase the market value of banks, and there is no strong and consistent evidence for a risk-reducing or risk-increasing effect. In terms of market value, I only find that business complexity is more valued by the markets, which is consistent with the diversification benefits found in Japan. For bank risk, there seem to be two opposing effects on the market-based risk measures and insolvency risk. On the one hand, business complexity is associated with lower variability in equity returns, suggesting that complexity can reduce bank risk. The risk-decline effects on market-based risk measures are more significant when the dynamics of the dependent variables are considered. On the other hand, all types of complexity tend to increase banks' insolvency risk, which indicates a stronger risk-taking incentive for complex banks.

When considering the moderating effect of bank governance, I find that higher board shareholding, larger boards, and fewer independent directors can reduce bank risk-taking behaviors, and these governance arrangements are expected to be more effective in mitigating the adverse effects of complexity. However, the results suggest that bank governance plays a minor role in moderating the effect of complexity on bank performance, especially with respect to risk. Conversely, some results suggest that higher board shareholding and large boards may exacerbate the adverse effects of complexity.

Regarding the channel analysis, I find that complexity is associated with higher income diversification and lower funding costs, which can explain the value-increasing effects and risk decline effects of bank complexity. However, business complex banks are found to be more opaque, while geographic complex banks are less opaque. Furthermore, I also find that small

banks gain little benefit and face more risk from a complexity strategy, while large banks are riskier when they become more complex in business.

This paper has several implications for bank managers, investors, and regulation authorities. First, banks should recognize the multifaceted impacts of complexity and understand that not all complexity can increase bank value. Small banks, in particular, should be more cautious when seeking international expansion, considering potential negative effects. Second, the approach of increasing the proportion of independent directors may not yield the anticipated benefits. Shareholders and regulatory authorities need to recognize that in the context of an immature market for independent directors or a non-U.S.-style board structure, an excessive emphasis on external oversight might adversely impact bank management, potentially worsening performance. Third, as it shows insignificant moderating effects of bank governance on complexity effects, banks should recognize the limited function of the board when adopting a complexity strategy and try to improve their governance in several ways.

Lastly, the analysis of this paper can be further discussed in (1) the construction of complexity metrics. I assume that every subsidiary is equally important to the group, which is inconsistent with the practice. Therefore, the complexity metrics can be constructed based on the weight of the subsidiaries, such as the assets or shareholdings. (2) identification. Employing proper IVs for both complexity and governance variables, or robust identification strategies, is essential to ensure the reliability of the results.

Tables

Table 4-1 Variable description

Variables	Description
Dependent variables	
Tobin's Q	Tobin's Q is defined as a ratio between market value and replacement costs of assets. It is calculated as: $\text{Tobin's Q} = \frac{\text{market value of equity} + \text{book value of debt}}{\text{book value of equity} + \text{book value of debt}}$
Total risk	The standard deviation of the bank stock returns during a fiscal year.
Systematic risk	The coefficients of the market index return in a market model.
logzscore	The natural logarithm of the Z-score. Z-score is calculated as: $Zscore = \frac{ROA + CAR}{\sigma_{ROA}}$
Independent variables	
Organizational complexity	The natural logarithm of the number of legal entities in a bank group.
Business complexity	
Count scope	The number of business scopes spanned by subsidiaries. Business scopes include banking, non-deposit money corporations, financial products transaction dealers and futures commodity transaction dealers, financial auxiliaries, other financial companies, and non-financial companies.
Count bank	The number of bank subsidiaries. For stand-alone banks, it is calculated as the number of bank subsidiaries (if any) plus 1 (itself).
Count non-fin	The number of non-financial companies.
Business HHI	$1 - \sum \left(\frac{\text{the number of subsidiaries in scope i}}{\text{the number of all subsidiaries}}\right)^2$, where i is the set of bank scopes defined before. For stand-alone banks, the denominator needs to be increased by 1 to adjust for the number of bank subsidiaries in the numerator.
Geographic complexity	
Foreign dummy	A dummy variable representing whether a bank group has foreign subsidiaries. This variable is equal to 1 if there is one or more foreign subsidiaries.
Count region	The number of regions spanned by subsidiaries. The subsidiaries located in tax-free islands, such as the British Virgin Islands and the Cayman Islands, are counted in the same group. For banks with no subsidiary, the number of regions is 1 (itself).
Count foreign	The number of foreign subsidiaries.
Geographic HHI	$1 - \sum \left(\frac{\text{the number of subsidiaries in region j}}{\text{the number of all subsidiaries}}\right)^2$, where j is the set of regions.
Governance	
Board shareholding	The ratio shareholding held by the board to outstanding shares.
Board size	The number of directors, including both insider and outsider directors.
Independent share	The ratio of the number of outsider directors to the total number of board members.
Controls	
Bank size	The natural logarithm of bank assets.
Capital ratio	The ratio of equity capital to total assets.

Loan-deposit ratio	The ratio of loans to deposits and negotiable certificates of deposit.
Asset growth rate	$(assets_t - assets_{t-1}) / assets_{t-1}$
Funding costs	Interest $expenses_t / ((deposit_{t-1}+deposit_t)/2)$
OHR	Overhead ratio. It is calculated by overhead costs / gross operating profits.
NPL	The ratio of non-performing loan. Non-performing loans refer to risk-monitored loans, including loans to borrowers in legal bankruptcy, past-due loans, loans in arrears by three months or more, and restructured loans.
ROA	Return on total assets. It is calcualted as: net $income_t / ((assets_{t-1}+assets_t)/2)$
Merger dummy	A dummy variable for bank merger. It is equal to 1 if the bank merger with another bank that does not belong to a same group in the current year.

Table 4-2 Principal component of business and geographic complexity

Business compexlity	BPC	Geographic compexlity	GPC
Count scope	0.5783	Foreign dummy	0.4451
Count bank	0.4910	Count region	0.5351
Count non-fin	0.4917	Count foreign	0.4793
Business HHI	0.4276	Geographic HHI	0.5346
Explained varaince	49.43%	Explained varaince	79.82%

Note: This table presents the results of principle component analysis on business and geographic complexity. The numbers in the table represent the eigenvectors of the first principal component. The last row reports the fraction of variance explained by the first component.

Table 4-3 Descriptive statistics

	N	Mean	SD	Min	Median	Max
Dependent variables						
Tobin's Q	1845	0.982	0.019	0.946	0.980	1.045
Total risk	1845	0.020	0.006	0.007	0.019	0.041
Systematic risk	1845	0.883	0.357	-0.037	0.925	1.627
logzscore	1643	4.231	1.396	0.475	4.480	7.143
Complexity						
Organizational complexity	1845	16.213	38.942	1	8	355
BPC	1845	0	1.406	-5.869	-0.031	8.621
Count scope	1845	4.941	1.115	1	5	6
Count bank	1845	1.485	1.727	1	1	15
Count non-fin	1845	3.200	3.413	0	3	36
Business HHI	1845	0.716	0.095	0	0.740	0.833
GPC	1845	0	1.787	-0.701	-0.701	11.866
Foreign dummy	1845	0.196	0.397	0	0	1
Count region	1845	1.655	2.183	1	1	20
Count foreign	1845	1.715	8.163	0	0	93
Geographic HHI	1845	0.069	0.168	0	0	0.784
Governance						
Board shareholding	1845	14.339	3.273	7	14	22
Board size	1845	0.269	0.126	0.062	0.250	0.688
Independent share	1835	0.003	0.004	0	0.001	0.028
Controls						
Bank size	1845	15.029	1.133	12.963	14.875	19.118
Capital ratio	1845	0.052	0.013	0.025	0.052	0.090
Loan-deposit ratio	1845	0.730	0.076	0.538	0.731	0.922
Asset growth rate	1845	0.028	0.046	-0.058	0.019	0.248
Funding costs	1845	0.002	0.002	0	0.001	0.012
OHR	1845	0.698	0.105	0.463	0.696	1.071
NPL	1845	0.041	0.026	0.009	0.033	0.133
ROA	1845	0.001	0.003	-0.017	0.002	0.008
Merger dummy	1845	0.008	0.090	0	0	1

Table 4-4 Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Organizational complexity	1.000														
(2) BPC	0.788	1.000													
(3) GPC	0.750	0.640	1.000												
(4) Board shareholding	-0.051	-0.149	-0.107	1.000											
(5) Board size	0.179	0.110	0.060	-0.022	1.000										
(6) Independent share	0.202	0.128	0.284	0.113	-0.412	1.000									
(7) Bank size	0.819	0.708	0.708	-0.260	0.284	0.245	1.000								
(8) Capital ratio	0.140	0.080	0.037	0.096	0.214	0.108	0.182	1.000							
(9) Loan-deposit ratio	0.062	-0.015	0.085	0.049	-0.284	0.090	-0.064	-0.051	1.000						
(10) Asset growth rate	0.090	0.092	0.041	-0.039	0.051	0.163	0.190	0.029	-0.064	1.000					
(11) Funding costs	0.510	0.317	0.534	0.036	0.116	-0.038	0.347	0.045	0.261	-0.106	1.000				
(12) OHR	-0.316	-0.249	-0.255	0.224	-0.094	0.122	-0.377	-0.243	-0.198	-0.018	-0.231	1.000			
(13) NPL	-0.146	-0.194	-0.150	0.061	-0.145	-0.403	-0.355	-0.293	0.157	-0.311	0.107	-0.147	1.000		
(14) ROA	0.112	0.107	0.091	-0.045	0.078	0.164	0.206	0.424	-0.076	0.240	-0.103	-0.261	-0.445	1.000	
(15) Merger dummy	0.094	0.091	0.053	-0.039	0.020	-0.004	0.097	-0.052	0.073	0.307	0.030	-0.022	-0.016	0.045	1.000

Table 4-5 Regression results for bank complexity and market value

	(1) Organizational	(2) Organizational	(3) Organizational	(4) Business	(5) Business	(6) Business	(7) Geographic	(8) Geographic	(9) Geographic
Complexity	0.0014		0.0024	0.0014**		0.0006	0.0003		0.0017*
	(0.0018)		(0.0019)	(0.0007)		(0.0008)	(0.0011)		(0.0010)
Complexity (instrumented)		-0.0004			0.0012**			0.0001	
		(0.0016)			(0.0006)			(0.0008)	
l.Tobin's Q			0.6332***			0.6322***			0.6101***
			(0.0496)			(0.0456)			(0.0416)
Bank size	-0.0024	-0.0004	-0.0001	-0.0031	-0.0019	0.0009	-0.0016	-0.0007	0.0002
	(0.0040)	(0.0029)	(0.0018)	(0.0039)	(0.0027)	(0.0013)	(0.0040)	(0.0027)	(0.0012)
Capital ratio	-0.5447***	-0.5440***	-0.0412	-0.5295***	-0.5288***	-0.0395	-0.5456***	-0.5451***	-0.0442
	(0.0831)	(0.0566)	(0.0545)	(0.0827)	(0.0567)	(0.0564)	(0.0838)	(0.0577)	(0.0558)
Loan-deposit ratio	0.0082	0.0065	-0.0070	0.0077	0.0065	-0.0043	0.0082	0.0066	0.0029
	(0.0090)	(0.0060)	(0.0088)	(0.0090)	(0.0060)	(0.0086)	(0.0092)	(0.0061)	(0.0089)
Asset growth rate	-0.0004	0.0006	-0.0072	-0.0002	0.0008	-0.0076	-0.0003	0.0006	-0.0049
	(0.0089)	(0.0075)	(0.0068)	(0.0088)	(0.0074)	(0.0068)	(0.0088)	(0.0075)	(0.0065)
Funding costs	-1.1212*	-1.1478***	-0.4148	-1.0584	-1.0424***	-0.2303	-1.1595*	-1.1343***	-0.8504
	(0.6754)	(0.3712)	(0.4630)	(0.6778)	(0.3684)	(0.4365)	(0.6804)	(0.3694)	(0.5538)
OHR	-0.0056	0.0021	-0.0060	-0.0056	0.0019	-0.0050	-0.0053	0.0020	-0.0069
	(0.0070)	(0.0041)	(0.0061)	(0.0070)	(0.0041)	(0.0058)	(0.0069)	(0.0041)	(0.0064)
NPL	-0.1230***	-0.1206***	-0.0663**	-0.1225***	-0.1247***	-0.0511*	-0.1191***	-0.1217***	-0.0761***
	(0.0432)	(0.0347)	(0.0320)	(0.0419)	(0.0343)	(0.0298)	(0.0417)	(0.0343)	(0.0268)
ROA	0.1494	0.1766	0.0345	0.1544	0.1812	0.0606	0.1529	0.1780	0.0119
	(0.1569)	(0.1604)	(0.1080)	(0.1553)	(0.1591)	(0.1186)	(0.1585)	(0.1614)	(0.1126)
Merger dummy	0.0017	0.0019	0.0060**	0.0015	0.0017	0.0056**	0.0017	0.0019	0.0051
	(0.0027)	(0.0027)	(0.0029)	(0.0027)	(0.0027)	(0.0023)	(0.0027)	(0.0027)	(0.0033)
Constant	1.0675***		0.3777***	1.0804***		0.3648***	1.0590***		0.3966***
	(0.0662)		(0.0544)	(0.0651)		(0.0521)	(0.0670)		(0.0481)
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
K-P Wald F		244.799			247.219			176.196	
Hansen J		0.416			0.212			0.804	
AR(2)			0.403			0.430			0.516
Hansen test			0.483			0.516			0.548
N	1723	1601	1723	1723	1601	1723	1723	1601	1723
R2(within)	0.7325			0.7339			0.7323		

Note: This table examines the relationship between bank complexity and market value. Columns (1) to (3) show the results for organizational complexity using the fixed effects model, 2SLS, and SYS-GMM, respectively, as do the other complexity variables. All variables are defined in Table 4-1. Specifications include bank, year-fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table 4-6 Regression results for bank complexity and risk

Panel A: Total risk

	(1) Organizational	(2) Organizational	(3) Organizational	(4) Business	(5) Business	(6) Business	(7) Geographic	(8) Geographic	(9) Geographic
Complexity	0.0000		-0.0021**	0.0000		-0.0009*	0.0002		-0.0003
	(0.0008)		(0.0010)	(0.0003)		(0.0005)	(0.0003)		(0.0003)
Complexity (instrumented)		0.0009			-0.0085*			0.0002	
		(0.0007)			(0.0048)			(0.0003)	
l.Total risk			0.4743***			0.4662***			0.4668***
			(0.0464)			(0.0433)			(0.0442)
Bank size	-0.0044**	-0.0055***	0.0010	-0.0045**	0.0052	0.0004	-0.0045**	-0.0050***	-0.0002
	(0.0020)	(0.0012)	(0.0008)	(0.0019)	(0.0058)	(0.0006)	(0.0019)	(0.0011)	(0.0006)
Capital ratio	-0.0856**	-0.0786***	-0.0022	-0.0852**	-0.1664***	0.0105	-0.0879**	-0.0804***	-0.0052
	(0.0358)	(0.0230)	(0.0270)	(0.0368)	(0.0551)	(0.0313)	(0.0360)	(0.0233)	(0.0262)
Loan-deposit ratio	0.0064	0.0072***	0.0021	0.0064	0.0081*	0.0015	0.0066	0.0073***	0.0002
	(0.0044)	(0.0028)	(0.0052)	(0.0044)	(0.0043)	(0.0049)	(0.0044)	(0.0028)	(0.0056)
Asset growth rate	0.0031	0.0036	-0.0003	0.0031	0.0023	0.0010	0.0031	0.0038	0.0011
	(0.0036)	(0.0029)	(0.0036)	(0.0036)	(0.0045)	(0.0037)	(0.0036)	(0.0029)	(0.0039)
Funding costs	0.5288***	0.6587***	0.5666**	0.5305***	-0.0904	0.5518**	0.5295***	0.6359***	0.5102**
	(0.1416)	(0.1433)	(0.2435)	(0.1443)	(0.3860)	(0.2633)	(0.1405)	(0.1430)	(0.2442)
OHR	-0.0042*	-0.0068***	-0.0032	-0.0042*	-0.0027	-0.0034	-0.0041*	-0.0066***	-0.0048**
	(0.0023)	(0.0019)	(0.0024)	(0.0023)	(0.0030)	(0.0026)	(0.0023)	(0.0019)	(0.0025)
NPL	0.0215	0.0164	0.0301*	0.0215	0.0424**	0.0209	0.0216	0.0190*	0.0209
	(0.0166)	(0.0108)	(0.0182)	(0.0160)	(0.0184)	(0.0194)	(0.0158)	(0.0104)	(0.0199)
ROA	-0.2175***	-0.2099***	-0.0842*	-0.2174***	-0.2485***	-0.0882	-0.2144***	-0.2071***	-0.1133**
	(0.0491)	(0.0598)	(0.0512)	(0.0490)	(0.0885)	(0.0548)	(0.0492)	(0.0606)	(0.0465)
Merger dummy	-0.0012	-0.0016*	0.0005	-0.0012	0.0001	0.0006	-0.0012	-0.0016*	0.0005
	(0.0010)	(0.0010)	(0.0011)	(0.0010)	(0.0016)	(0.0011)	(0.0010)	(0.0009)	(0.0011)
Constant	0.0841***		-0.0038	0.0845***		0.0011	0.0853***		0.0116
	(0.0316)		(0.0125)	(0.0303)		(0.0104)	(0.0307)		(0.0109)
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
K-P Wald F		244.799			6.173			176.196	
Hansen J		0.126			One IV			1.166	
AR(2)			0.877			0.893			0.861
Hansen test			0.548			0.429			0.415
N	1723	1601	1723	1723	1723	1723	1723	1601	1723
R2(within)	0.5358			0.5358			0.5361		

(Continued on next page)

Table 4-6 (Continued)

Panel B: Systematic risk

	(1) Organizational	(2) Organizational	(3) Organizational	(4) Business	(5) Business	(6) Business	(7) Geographic	(8) Geographic	(9) Geographic
Complexity	0.0287		-0.1114*	0.0124		0.0098	0.0152		-0.0432***
	(0.0378)		(0.0587)	(0.0146)		(0.0279)	(0.0208)		(0.0150)
Complexity (instrumented)		0.0275 (0.0347)			0.0005 (0.0155)			0.0240 (0.0166)	
l.Systematic risk			0.5309***			0.5155***			0.4752***
			(0.0422)			(0.0441)			(0.0445)
Bank size	-0.0694	-0.1169*	0.1636***	-0.0653	-0.1001	0.0862***	-0.0577	-0.1111*	0.1346***
	(0.0883)	(0.0668)	(0.0307)	(0.0854)	(0.0626)	(0.0303)	(0.0848)	(0.0602)	(0.0278)
Capital ratio	-2.4628	-2.4612**	-0.9226	-2.3083	-2.4422**	-1.0903	-2.5813	-2.6953**	-1.1599
	(1.6024)	(1.0902)	(2.1284)	(1.6253)	(1.1153)	(2.0574)	(1.5916)	(1.0893)	(1.8269)
Loan-deposit ratio	0.5925**	0.6249***	0.2414	0.5858**	0.6200***	0.1982	0.6025**	0.6423***	0.0999
	(0.2447)	(0.1495)	(0.3296)	(0.2431)	(0.1494)	(0.2900)	(0.2451)	(0.1500)	(0.2581)
Asset growth rate	-0.1835	-0.0582	-0.2315	-0.1811	-0.0558	-0.2316	-0.1792	-0.0490	-0.3261
	(0.2067)	(0.1609)	(0.2397)	(0.2080)	(0.1611)	(0.2213)	(0.2111)	(0.1618)	(0.2179)
Funding costs	32.4102***	37.3970***	-4.8386	32.4854***	36.6139***	-13.3701	31.6781***	37.1222***	1.8685
	(7.3996)	(7.5749)	(11.7953)	(7.4262)	(7.5583)	(9.7453)	(7.5680)	(7.5642)	(11.1242)
OHR	-0.1852*	-0.2196**	-0.1269	-0.1819*	-0.2142**	-0.1333	-0.1758	-0.2103**	-0.1433
	(0.1050)	(0.0872)	(0.1042)	(0.1057)	(0.0872)	(0.1093)	(0.1063)	(0.0874)	(0.1199)
NPL	-0.0205	0.1063	1.0204	0.0315	0.1833	0.6376	0.0594	0.1732	0.9947
	(0.6959)	(0.5230)	(0.8802)	(0.7023)	(0.5158)	(0.7879)	(0.6993)	(0.5129)	(0.7200)
ROA	-2.5605	-2.8825	0.3776	-2.5185	-2.8853	-0.3025	-2.3532	-2.5562	1.1244
	(2.8240)	(2.9003)	(3.5198)	(2.8179)	(2.9059)	(2.7440)	(2.7886)	(2.9119)	(3.2994)
Merger dummy	-0.0553	-0.0838	0.0198	-0.0574	-0.0844	0.0178	-0.0531	-0.0784	0.0245
	(0.0409)	(0.0569)	(0.0718)	(0.0413)	(0.0567)	(0.0584)	(0.0402)	(0.0557)	(0.0792)
Constant	1.0996		-1.9387***	1.0936		-0.9112*	0.9811		-1.5456***
	(1.2972)		(0.5248)	(1.2668)		(0.5240)	(1.2649)		(0.4917)
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
K-P Wald F		244.799			247.219			176.196	
Hansen J		0.112			1			2.954*	
AR(2)			0.143			0.191			0.244
Hansen test			0.368			0.452			0.392
N	1723	1601	1723	1723	1601	1723	1723	1601	1723
R2(within)	0.5024			0.5024			0.5361		

(Continued on next page)

Table 4-6 (Continued)

Panel C: Insolvency risk

	(1) Organizational	(2) Organizational	(3) Organizational	(4) Business	(5) Business	(6) Business	(7) Geographic	(8) Geographic	(9) Geographic
Complexity	-0.1988		-0.4594**	-0.1396*		-0.2244*	-0.0671		-0.1301
	(0.1563)		(0.2180)	(0.0723)		(0.1190)	(0.0757)		(0.0834)
Complexity (instrumented)		-0.0029			-0.0071			-0.1508**	
		(0.1754)			(0.0753)			(0.0684)	
l.logzscore			0.4667***			0.4571***			0.4741***
			(0.0390)			(0.0385)			(0.0366)
Bank size	0.1886	0.1986	0.1929	0.2177	0.2040	0.0833	0.0919	0.2688	-0.0103
	(0.4465)	(0.2641)	(0.1625)	(0.4137)	(0.2509)	(0.1627)	(0.4314)	(0.2415)	(0.1238)
Capital ratio	37.3816***	36.5688***	5.0399	35.6252***	36.4791***	4.1706	38.0323***	38.1226***	4.7187
	(8.2169)	(5.4374)	(7.8900)	(8.2225)	(5.5166)	(8.8383)	(8.2536)	(5.4664)	(7.2383)
Loan-deposit ratio	-2.9130***	-2.8497***	0.2213	-2.8484***	-2.8487***	0.8224	-2.9289***	-2.9892***	-0.7634
	(0.9988)	(0.6538)	(1.3402)	(0.9889)	(0.6536)	(1.3391)	(0.9884)	(0.6608)	(1.1372)
Asset growth rate	-0.1605	-0.3197	-0.7141	-0.1840	-0.3212	-0.5633	-0.1815	-0.3633	-0.8337
	(0.9780)	(0.8064)	(0.8314)	(0.9725)	(0.8055)	(0.8675)	(0.9847)	(0.8039)	(0.9070)
Funding costs	-31.7682	-34.6372	-24.9572	-36.5549	-35.0947	-20.1808	-26.5871	-37.9721	-17.7362
	(30.5922)	(27.1785)	(46.4560)	(31.3251)	(27.5614)	(59.9881)	(31.2619)	(27.1154)	(38.5843)
OHR	-0.7087	-0.4859	-1.0663*	-0.7239	-0.4861	-1.0527*	-0.7530	-0.5112	-1.0633**
	(0.5726)	(0.4297)	(0.5557)	(0.5723)	(0.4266)	(0.5618)	(0.5714)	(0.4298)	(0.5143)
NPL	-6.1283	-6.6746**	-2.5400	-6.3741*	-6.6652**	-3.8850	-6.6737*	-6.6115**	-3.2171
	(3.7381)	(3.0150)	(4.5551)	(3.7645)	(2.9218)	(4.6562)	(3.7726)	(2.9134)	(4.6884)
ROA	67.3579***	68.4542***	31.7551***	66.6542***	68.4289***	31.3566***	66.5282***	66.3743***	30.4059***
	(10.7806)	(10.3956)	(11.9495)	(10.8708)	(10.4179)	(11.5442)	(10.8593)	(10.5181)	(10.9291)
Merger dummy	-0.5500***	-0.5059***	-0.8421**	-0.5217***	-0.5047***	-0.9182***	-0.5647***	-0.5432***	-0.7515*
	(0.1607)	(0.1858)	(0.3460)	(0.1509)	(0.1857)	(0.3501)	(0.1563)	(0.1869)	(0.3882)
Constant	2.3832		1.1283	1.5878		1.4493	3.4079		3.8897*
	(6.7023)		(2.6981)	(6.3694)		(2.9909)	(6.5351)		(2.2978)
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
K-P Wald F		244.799			247.219			176.196	
Hansen J		0.266			1.351			2.522	
AR(2)			0.533			0.513			0.535
Hansen test			0.122			0.130			0.105
N	1625	1601	1521	1625	1601	1521	1625	1601	1521
R2(within)	0.4909			0.4924			0.4906		

Note: This table examines the relationship between bank complexity and risk. Panels A, B, and C present results for total risk, systematic risk, and insolvency risk, respectively. In each panel, Columns (1) to (3) show the results for organizational complexity using the fixed effects model, 2SLS, and SYS-GMM, respectively, as do the other complexity variables. All variables are defined in Table 4-1. Specifications include bank and year fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table 4-7 Regression results for bank governance and performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Tobin's Q	Tobin's Q	Tobin's Q	Total risk	Total risk	Total risk	Systematic risk	Systematic risk	Systematic risk	logzscore	logzscore	logzscore
Board shareholding	0.0940			-0.2540***			-8.5341***			33.4102**		
	(0.0810)			(0.0812)			(2.2763)			(13.6329)		
Board size		0.0001			-0.0002***			-0.0099**			-0.0125	
		(0.0002)			(0.0001)			(0.0041)			(0.0174)	
Independent share			-0.0087			0.0069**			0.1426			-0.4820
			(0.0078)			(0.0032)			(0.1324)			(0.5547)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	1723	1723	1723	1723	1723	1723	1723	1723	1723	1625	1625	1625
R2(within)	0.7324	0.7324	0.7331	0.5445	0.5398	0.5400	0.5063	0.5060	0.5027	0.4928	0.4903	0.4904

Note: This table examines the relationship between bank governance and performance. Controls include Bank size, Capital ratio, Loan-deposit ratio, Asset growth rate, Funding costs, OHR, NPL, ROA, and Merger dummy. All variables are defined in Table 4-1. Specifications include bank and year fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table 4-8 Regression results for moderating effects of governance

Panel A: Tobin's Q									
	(1) Organizational	(2) Organizational	(3) Organizational	(4) Business	(5) Business	(6) Business	(7) Geographic	(8) Geographic	(9) Geographic
Complexity * Board shareholding	0.0278			0.0129			0.2014		
	(0.0658)			(0.0951)			(0.2545)		
* Board size		-0.0007***			-0.0003***			-0.0004***	
		(0.0002)			(0.0001)			(0.0001)	
* Independent share			0.0060			-0.0137***			0.0022
			(0.0047)			(0.0049)			(0.0029)
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
K-P Wald F	134.771	194.69	126.158	130.575	114.284	44.011	37.793	101.711	88.528
Hansen J	0.549	1.164	4.259	1.423	4.425	0.054	3.197	2.566	2.070
N	1601	1601	1601	1601	1601	1601	1601	1601	1601
Panel B: Total risk									
	(1) Organizational	(2) Organizational	(3) Organizational	(4) Business	(5) Business	(6) Business	(7) Geographic	(8) Geographic	(9) Geographic
Complexity * Board shareholding	0.0432			-0.0251			0.0212		
	(0.0328)			(0.0677)			(0.0809)		
* Board size		0.0001			0.0000			0.0000	
		(0.0001)			(0.0001)			(0.0000)	
* Independent share			-0.0016			-0.0027			-0.0005
			(0.0020)			(0.0024)			(0.0011)
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
K-P Wald F	134.771	194.69	126.158	130.575	114.284	44.011	37.793	101.711	88.528
Hansen J	0.050	0.397	0.286	7.791**	5.789*	2.261	2.815	6.417**	7.756**
N	1601	1601	1601	1601	1601	1601	1601	1601	1601

(Continued on next page)

Table 4-8 (Continued)

Panel C: Systematic risk									
	(1) Organizational	(2) Organizational	(3) Organizational	(4) Business	(5) Business	(6) Business	(7) Geographic	(8) Geographic	(9) Geographic
Complexity * Board shareholding	0.8633			-3.0244			-1.5260		
	(1.8033)			(3.4445)			(4.8434)		
* Board size		0.0003			0.0015			0.0012	
		(0.0037)			(0.0025)			(0.0019)	
* Independent share			0.0240			-0.1030			-0.0567
			(0.1120)			(0.1248)			(0.0627)
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
K-P Wald F	134.771	194.69	126.158	130.575	114.284	44.011	37.793	101.711	88.528
Hansen J	0.380	0.605	0.832	3.982	2.382	0.588	2.683	4.614*	3.745
N	1601	1601	1601	1601	1601	1601	1601	1601	1601
Panel D: insolvency risk									
	(1) Organizational	(2) Organizational	(3) Organizational	(4) Business	(5) Business	(6) Business	(7) Geographic	(8) Geographic	(9) Geographic
Complexity * Board shareholding	-11.5747**			-25.8969**			-32.1818		
	(5.0222)			(11.2826)			(20.5820)		
* Board size		-0.0087			-0.0025			0.0042	
		(0.0143)			(0.0109)			(0.0069)	
* Independent share			0.4620			0.3656			-0.3408
			(0.4740)			(0.5470)			(0.2547)
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
K-P Wald F	134.771	194.69	126.158	11.304	114.284	44.011	37.793	101.711	88.528
Hansen J	2.162	0533	0.343	1.382	1.469	0.892	3.380	4.134	3.975
N	1601	1601	1601	1601	1601	1601	1601	1601	1601

Note: This table examines the moderating effects of bank governance with instrumented complexity variables and their interaction terms. Panels A, B, C, and D present results for Tobin's Q, total risk, systematic risk, and insolvency risk, respectively. Only the coefficients of the interaction terms between complexity and governance are reported. Controls include complexity, governance, and other control variables (Bank size, Capital ratio, Loan-deposit ratio, Asset growth rate, Funding costs, OHR, NPL, ROA, and Merger dummy). All variables are defined in Table 4-1. Specifications include bank and year fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table 4-9 Robustness: complexity effects with alternative measures for bank performance and Lewbel (2012) model

	(1)	(2)	(3)	(4)	(5)	(6)
	M/B	M/B	M/B	Idiosyncratic risk	Idiosyncratic risk	Idiosyncratic risk
(instrumented)						
Organizational	-0.0200			-0.0042**		
	(0.0877)			(0.0020)		
Business		0.0346*			-0.0011*	
		(0.0204)			(0.0007)	
Geographic			0.0557			-0.0001
			(0.0361)			(0.0007)
Controls	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
K-P Wald F	4.119	6.172	2.469	4.119	6.173	2.469
Hansen J	17.879	28.790	17.766	18.502	31.682	32.302
N	1723	1723	1723	1723	1723	1723

Note: This table examines the relationship between alternative bank performance measures and complexity. The dependent variables are the market-to-book ratio and Idiosyncratic risk. Following Lewbel (2012), complexity variables are instrumented by the average complexity level of competitors and generated heteroskedasticity-based instruments from the error structure of the first-stage IV regression. Controls include Bank size, Capital ratio, Loan-deposit ratio, Asset growth rate, Funding costs, OHR, NPL, ROA, and Merger dummy. All variables are defined in Table 4-1. Specifications include bank and year fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table 4-10 Robustness: moderating effects with alternative measures for bank performance and Lewbel (2012) model

Panel A: Market-to-book ratio

	(1) Organizational	(2) Organizational	(3) Organizational	(4) Business	(5) Business	(6) Business	(7) Geographic	(8) Geographic	(9) Geographic
Complexity * Board shareholding	-0.6054			0.2065			-1.2905		
	(1.0392)			(1.6032)			(1.0894)		
* Board size		-0.0161***			-0.0081***			-0.0094***	
		(0.0039)			(0.0428)			(0.0023)	
* Independent share			0.1055			0.0195			0.0418
			(0.1172)			(0.0794)			(0.0746)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
K-P Wald F	6.249	2.951	4.037	5.574	6.238	7.934	5.164	1.605	5.260
Hansen J	48.257	62.107	44.489	46.858	63.506	49.536	57.273	35.540	37.213
N	1723	1723	1601	1723	1723	1723	1723	1723	1723

Panel B: Idiosyncratic risk

	(1) Organizational	(2) Organizational	(3) Organizational	(4) Business	(5) Business	(6) Business	(7) Geographic	(8) Geographic	(9) Geographic
Complexity * Board shareholding	0.0736**			0.0309			0.0414		
	(0.0311)			(0.0661)			(0.0560)		
* Board size		0.0001			0.0001**			-0.0001**	
		(0.0001)			(0.0001)			(0.0000)	
* Independent share			-0.0011			-0.0013			-0.0009
			(0.0025)			(0.0019)			(0.0013)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
K-P Wald F	6.249	2.951	4.037	5.574	6.238	7.934	5.164	1.605	5.260
Hansen J	56.324	41.800	67.396	74.635*	55.642	61.918	73.034*	50.200	68.828
N	1723	1723	1723	1723	1723	1723	1723	1723	1723

Note: This table examines the moderating effects of bank governance with alternative bank performance measures. Panels A and B present the results for market-to-book ratio and Idiosyncratic risk, respectively. Only the coefficients of the interaction terms between complexity and governance are reported. Following Lewbel (2012), complexity variables are instrumented by the average complexity level of competitors and generated heteroskedasticity-based instruments from the error structure of the first-stage IV regression. Controls include complexity, governance, and other control variables (Bank size, Capital ratio, Loan-deposit ratio, Asset growth rate, Funding costs, OHR, NPL, ROA, and Merger dummy). All variables are defined in Table 4-1. Specifications include bank and year fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table 4-11 Robustness: nonlinear relationships

	(1) Tobin's Q	(2) Tobin's Q	(3) Tobin's Q	(4) Total risk	(5) Total risk	(6) Total risk	(7) Systematic risk	(8) Systematic risk	(9) Systematic risk	(10) logzscore	(11) logzscore	(12) logzscore
(instrumented) Organizational	0.0069**			0.0001			-0.0495			-0.3103		
	(0.0033)			(0.0018)			(0.0733)			(0.3478)		
Square of Organizational	-0.0017**			0.0002			0.0179			0.0718		
	(0.0009)			(0.0003)			(0.0159)			(0.0710)		
Business		0.0017			0.0005			0.0259			-0.0113	
		(0.0011)			(0.0004)			(0.0225)			(0.1029)	
Square of business		0.0002			0.0000			0.0095*			-0.0005	
		(0.0003)			(0.0001)			(0.0055)			(0.0219)	
Geographic			0.0010			0.0002			0.0163			-0.1047
			(0.0007)			(0.0003)			(0.0165)			(0.0731)
Square of geographic			-0.0004*			0.0000			0.0031			-0.0193
			(0.0002)			(0.0001)			(0.0060)			(0.0196)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
K-P Wald F	97.765	48.167	5.563	97.765	48.167	4.226	97.765	48.167	4.226	97.765	48.167	4.226
Hansen J	2.501	0.051	1.112	3.471	3.928**	2.70	0.059	0.299	3.404	3.452	1.461	3.888
N	1601	1601	1601	1601	1601	1601	1601	1601	1601	1601	1601	1601

Note: This table examines the possible nonlinear relationships between bank performance and complexity. Controls include Bank size, Capital ratio, Loan-deposit ratio, Asset growth rate, Funding costs, OHR, NPL, ROA, and Merger dummy. All variables are defined in Table 4-1. Specifications include bank and year fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table 4-12 Channels analysis of complexity effects

	(1) Non-interest	(2) Non-interest	(3) Non-interest	(4) Funding costs	(5) Funding costs	(6) Funding costs	(7) Opacity	(8) Opacity	(9) Opacity
(instrumented)									
Organizational	0.0346***			-0.0007***			-0.0009		
	(0.0072)			(0.0002)			(0.0007)		
Business		0.0191***			-0.0002***			-0.0006**	
		(0.0033)			(0.0001)			(0.0002)	
Geographic			0.0054*			-0.0001			0.0007**
			(0.0029)			(0.0001)			(0.0003)
Controls	YES	YES	YES	YES	YES				
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
K-P Wald F	239.615	256.249	178.284	249.350	270.391	179.617	239.615	256.249	178.284
Hansen J	1.674	0.848	1.064	0.261	1.366	0.626	0.005	0.606	5.746**
N	1601	1601	1601	1601	1601	1601	1601	1601	1601

Note: This table examines the possible channels that may explain the impacts of complexity on bank performance. The dependent variables are non-interest income ratio, funding costs, and opacity, measured by the ratio of AFS security to total assets. Controls include Bank size, Capital ratio, Loan-deposit ratio, Asset growth rate, Funding costs (not in columns 4, 5, and 6), OHR, NPL, ROA, and Merger dummy. All variables are defined in Table 4-1. Specifications include bank and year fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table 4-13 Heterogeneity: bank size and complexity effects

Panel A: Small banks												
	(1) Tobin's Q	(2) Tobin's Q	(3) Tobin's Q	(4) Total risk	(5) Total risk	(6) Total risk	(7) Systematic risk	(8) Systematic risk	(9) Systematic risk	(10) logzscore	(11) logzscore	(12) logzscore
(instrumented)												
Organizational	0.0004			0.0028*			0.0983			-0.2396		
	(0.0018)			(0.0014)			(0.0598)			(0.2848)		
Business		0.0007			0.0008			-0.0068			-0.0388	
		(0.0007)			(0.0006)			(0.0232)			(0.1091)	
Geographic			-0.0019*			0.0017***			0.1065***			-0.1020
			(0.0010)			(0.0005)			(0.0305)			(0.1414)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
K-P Wald F	252.451	133.488	98.147	252.451	133.488	98.147	252.451	133.488	98.147	252.451	133.488	98.147
Hansen J	1.969	0.498	0.201	0.079	0.700	0.261	0.629	0.338	0.493	0.482	2.103	0.213
N	778	778	778	778	778	778	778	778	778	778	778	778
Panel A: Large banks												
	(1) Tobin's Q	(2) Tobin's Q	(3) Tobin's Q	(4) Total risk	(5) Total risk	(6) Total risk	(7) Systematic risk	(8) Systematic risk	(9) Systematic risk	(10) logzscore	(11) logzscore	(12) logzscore
(instrumented)												
Organizational	0.0010			0.0007			0.0057			0.0698		
	(0.0029)			(0.0008)			(0.0483)			(0.2618)		
Business		0.0027**			0.0051***			0.2322***			-0.0947	
		(0.0012)			(0.0018)			(0.0897)			(0.1160)	
Geographic			0.0009			0.0001			0.0147			-0.2143***
			(0.0009)			(0.0003)			(0.0184)			(0.0817)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
K-P Wald F	65.872	70.202	107.476	65.782	11.119	107.476	65.872	11.119	107.476	65.872	70.202	107.476
Hansen J	0.957	0.101	1.311	1.104	One IV	0.848	0.604	One IV	2.831*	1.625	0.157	3.658*
N	818	818	818	818	818	818	818	818	818	818	818	818

Note: This table examines the impact of bank complexity on the performance of small and large banks. Panels A and B present the results for small and large banks, respectively. Small (large) banks are defined as banks with total assets below (over) the average assets each year. Controls include Bank size, Capital ratio, Loan-deposit ratio, Asset growth rate, Funding costs, OHR, NPL, ROA, and Merger dummy. All variables are defined in Table 4-1. Specifications include bank and year fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Table 4-14 Heterogeneity: bank size and governance effects

Panel A: Small banks												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Tobin's Q	Tobin's Q	Tobin's Q	Total risk	Total risk	Total risk	Systematic risk	Systematic risk	Systematic risk	logzscore	logzscore	logzscore
Board shareholding	-0.0011			-0.2664***			-8.5745***			44.1396***		
	(0.0840)			(0.0882)			(2.5701)			(16.0231)		
Board size		0.0003			-0.0002*			-0.0127			0.0031	
		(0.0002)			(0.0001)			(0.0078)			(0.0320)	
Independent share			-0.0129***			0.0038			0.0754			-0.3174
			(0.0048)			(0.0040)			(0.1505)			(0.7861)
N	851	851	851	851	851	851	851	851	851	794	794	794
R2(within)	0.7554	0.7562	0.7577	0.4945	0.4844	0.4818	0.5274	0.5259	0.5219	0.5173	0.5106	0.5108
Panel B: Large banks												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Tobin's Q	Tobin's Q	Tobin's Q	Total risk	Total risk	Total risk	Systematic risk	Systematic risk	Systematic risk	logzscore	logzscore	logzscore
Board shareholding	0.2071			-0.2893**			-10.1460*			16.1774		
	(0.3142)			(0.1335)			(5.8935)			(20.7685)		
Board size		-0.0000			-0.0002**			-0.0105**			-0.0189	
		(0.0003)			(0.0001)			(0.0050)			(0.0202)	
Independent share			-0.0006			0.0079***			0.2198			0.0816
			(0.0109)			(0.0028)			(0.1787)			(0.8134)
N	872	872	872	872	872	872	872	872	872	831	831	831
R2(within)	0.7467	0.7465	0.7465	0.7395	0.7409	0.7403	0.5456	0.5488	0.5448	0.4730	0.4735	0.4727

Note: This table examines the impact of bank governance on the performance of small and large banks. Panels A and B present the results for small and large banks, respectively. Small (large) banks are defined as banks with total assets below (over) the average assets each year. Controls include Bank size, Capital ratio, Loan-deposit ratio, Asset growth rate, Funding costs, OHR, NPL, ROA, and Merger dummy. All variables are defined in Table 4-1. Specifications include bank and year fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Figures

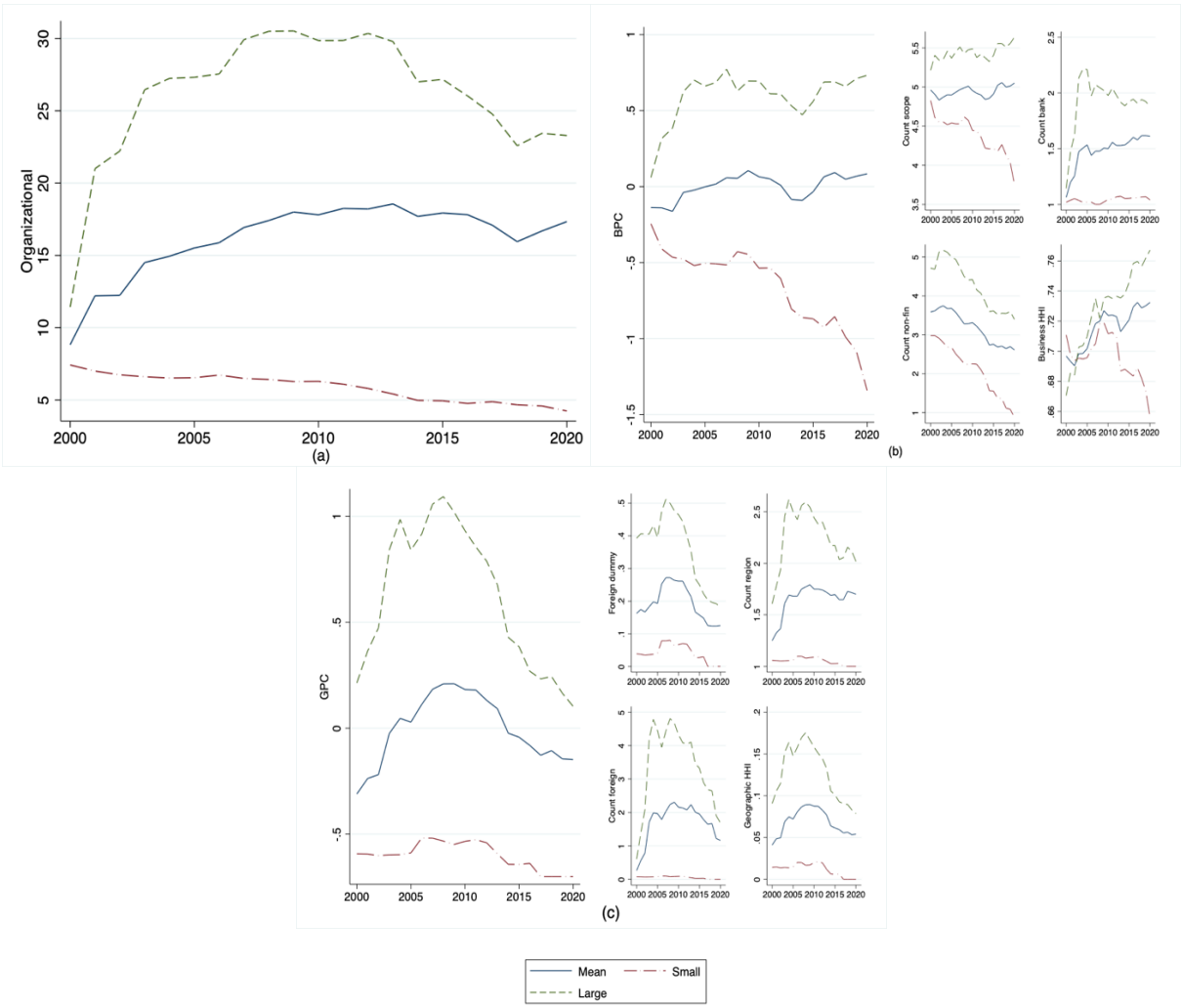

Figure 4-1 The evolution of bank complexity
Note: This figure shows the average value of bank complexity for the whole sample, small and large banks, from 2000 to 2020. Small (large) banks are defined as banks with total assets below (over) the average assets each year. The complexity variables are defined in Table 4-1.

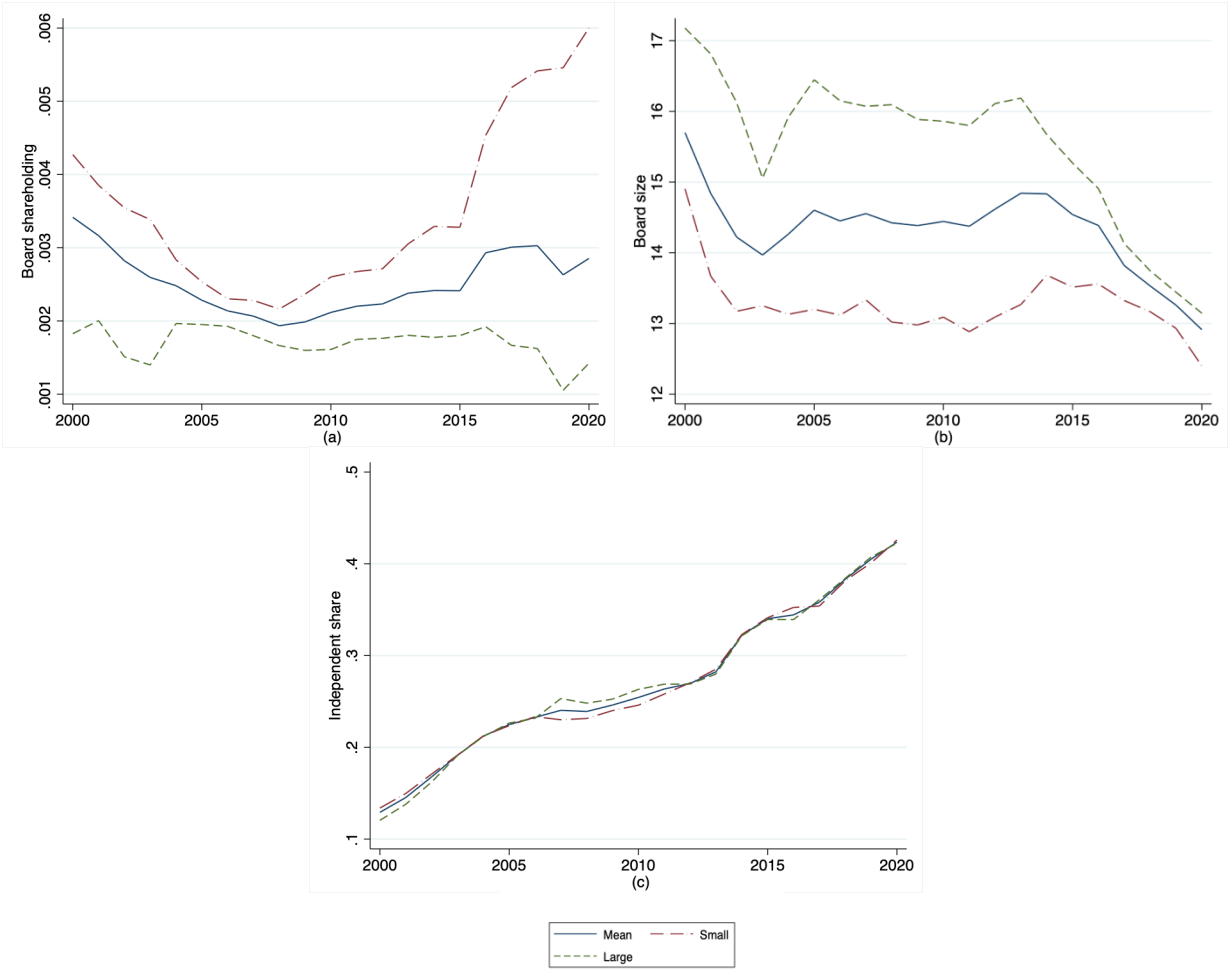

Figure 4-2 The evolution of bank governance

Note: This figure shows the average value of bank governance for the whole sample, small and large banks, from 2000 to 2020. Small (large) banks are defined as banks with total assets below (over) the average assets each year. The governance variables are defined in Table 4-1.

Appendix 1

The database provides some basic information about bank subsidiaries, including company name, location, business content, and shareholding ratio (direct and indirect). To determine the industry to which a subsidiary belongs, I refer to the Japan Standard Industrial Classification (Reversion 13). This classification system categorizes the industry into four levels: Class, Group, Major group, and Division. The classification of bank subsidiaries is determined at the Group level due to the overlaps in operations. Under the Division J Finance and Insurance, there are 6 Major groups, and the detailed information for each Major group is listed below. However, as banking groups have few subsidiaries that can be classified as Major groups 63 and 67, I consolidate these subsidiaries and other companies that are engaged in financial operations but are difficult to classify into any other Major groups, such as lease, in a new group, other financial companies. Subsidiaries engaged in labor brokering, real estate, IT, and other business operations are classified as non-financial companies. Therefore, the bank subsidiaries are divided into six groups: banking, non-deposit money corporations, financial products and future commodity transaction dealers, financial auxiliaries, other financial companies, and non-financial companies.

Table A4-1 Japan Standard Industrial Classification for the finance industry

Classification	Description (collected from the official documents)
Division J FINANCE AND INSURANCE	
62 BANKING	Central bank and banks that deal with savings and are engaged in banking or trust banking.
63 FINANCIAL INSTITUTIONS FOR COOPERATIVE ORGANIZATIONS	Financial institutions primarily engaged in dealing with savings and offering financial services for small businesses, farmers and fishermen who are members of cooperative organizations and for labor organizations and cooperative organizations.
64 NON-DEPOSIT MONEY CORPORATIONS, INCLUDING LENDING AND CREDIT CARD BUSINESS	Credit institutions that do not deal with savings, including credit and finance businesses, pawnbrokers, credit card institutions, Government-related financial institutions.
65 FINANCIAL PRODUCTS TRANSACTION DEALERS AND FUTURES COMMODITY TRANSACTION DEALERS	Establishments engaged in intermediating financial transactions such as financial products transaction activities, futures commodity transactions, commodity investment advisory, and the like.
66 FINANCIAL AUXILIARIES	Establishments engaged in auxiliary or incidental operations closely related to operations that are conducted by deposit handling institutions such as banks, non-deposit money corporations such as credit and finance businesses, financial products transaction brokers

	and dealers, futures commodity transaction dealers, and trust business, financial brokers and intermediaries.
67 INSURANCE INSTITUTIONS, INCLUDING INSURANCE AGENTS, BROKERS AND SERVICES	Establishments engaged in any forms of insurance business, insurance agents and brokers, insurance companies and those engaged in providing insurance subscribers with insurance services. Establishments engaged in mutual aid enterprise related to agriculture or fisheries and those engaged in fishing boat insurance are classified in this group.

For specific classification operations, I use some keywords extracted from the description of each Major group and Class to identify the industries of the subsidiaries. Specifically, if a subsidiary's company name or business content includes these keywords, it will be categorized into this group. For example, for Major Group 62, “bank (Ginkou)” is its core keyword. If the keyword “bank (Ginkou)” is in the company name or business content, it is considered a bank. However, this classification is somewhat rudimentary, as a firm engaged in banking-related business might be inaccurately categorized. To address this issue, I implement several verification procedures. Firstly, I assign priorities to keywords; for instance, if a company is identified as a bank, it cannot be classified into other groups simultaneously. Secondly, in cases where a subsidiary falls into two or more groups, I meticulously examine each classification to ensure accuracy. It's worth noting that certain companies engage in various financial businesses simultaneously. In such instances, they are allowed to be classified into multiple groups, while it will be counted as 1/n (n is the number of groups that it belongs to) to avoid double counting.

Appendix 2

Table A4-2 Regression results for instrumented bank governance and performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(instrumented)	Tobin's Q	Tobin's Q	Tobin's Q	Total risk	Total risk	Total risk	Systematic risk	Systematic risk	Systematic risk	logzscore	logzscore	logzscore
Board shareholding	0.0287			-0.3065***			-14.4219***			35.7385***		
	(0.1172)			(0.0771)			(3.9267)			(12.8576)		
Board size		0.0001			-0.0002**			-0.0129***			-0.0085	
		(0.0002)			(0.0001)			(0.0043)			(0.0212)	
Independent share			-0.0105			0.0067**			0.1669			-0.3563
			(0.0066)			(0.0027)			(0.1395)			(0.7303)
K-P Wald F	132.429	401.012	289.261	132.429	401.012	289.261	132.429	401.012	289.261	132.429	401.012	289.261
Hansen J	3.832*	2.104	1.932	11.1118***	0.187	0.221	3.441*	0.313	0.566	0.005	0.016	0.073
N	1601	1601	1601	1601	1601	1601	1601	1601	1601	1601	1601	1601

Note: This table examines the relationship between instrumented bank governance and performance. Governance variables are instrumented by the average governance level of competitors and the two-year lagged independent variable. Controls include Bank size, Capital ratio, Loan-deposit ratio, Asset growth rate, Funding costs, OHR, NPL, ROA, and Merger dummy. All variables are defined in Table 4-1. Specifications include bank and year fixed effects, and robust standard errors clustered at the bank level. Robust standard errors are in parentheses. The superscripts ∗, ∗∗, ∗∗∗ denote statistically significant results at the 10%, 5%, and 1% levels, respectively.

Reference

Adams, R. B. and D. Ferreira (2007), A theory of friendly boards, *The Journal of Finance,* 62**,** 217-50.

Adams, R. B. and H. Mehran (2012), Bank board structure and performance: Evidence for large bank holding companies, *Journal of Financial Intermediation,* 21**,** 243-67.

Afonso, G., J. A. Santos and J. Traina (2014), Do'Too-Big-To-Fail'Banks Take on More Risk?, *Economic Policy Review,* 20**,** 41-58.

Aldasoro, I., B. Hardy and M. Jager (2022), The Janus face of bank geographic complexity, *Journal of Banking & Finance,* 134**,** 106040.

Aman, H. and P. Nguyen (2012), The size and composition of corporate boards in Japan, *Asian Business & Management,* 11**,** 425-44.

Arellano, M. and O. Bover (1995), Another look at the instrumental variable estimation of error-components models, *Journal of Econometrics,* 68**,** 29-51.

Argimón, I. and M. Rodríguez-Moreno (2022), Risk and control in complex banking groups, *Journal of Banking & Finance,* 134**,** 106038.

Ashcraft, A. B. (2008), Are bank holding companies a source of strength to their banking subsidiaries?, *Journal of Money, Credit and Banking,* 40**,** 273-94.

Avraham, D., P. Selvaggi and J. I. Vickery (2012), A structural view of US bank holding companies, *Economic Policy Review,* 18**,** 65-81.

Baele, L., O. De Jonghe and R. Vander Vennet (2007a), Does the stock market value bank diversification?, *Journal of Banking & Finance,* 31**,** 1999-2023.

Baele, L., O. De Jonghe and R. V. Vennet (2007b), Does the Stock Market Value Bank Diversification, *Journal of Banking & Finance,* 31**,** 1999-2023.

Bai, G. and E. Elyasiani (2013), Bank stability and managerial compensation, *Journal of Banking & Finance,* 37**,** 799-813.

Blau, B. M., T. J. Brough and T. G. Griffith (2017), Bank opacity and the efficiency of stock prices, *Journal of Banking & Finance,* 76**,** 32-47.

Blundell, R. and S. Bond (1998), Initial conditions and moment restrictions in dynamic panel data models, *Journal of Econometrics,* 87**,** 115-43.

Board, F. S. (2013), Global Systemically Important Banks-Updated Assessment Methodology and the Higher Loss Absorbency Requirement, *Revised version July*.

Boone, A. L., L. C. Field, J. M. Karpoff and C. G. Raheja (2007), The determinants of corporate board size and composition: An empirical analysis, *Journal of Financial Economics,* 85**,** 66-101.

Brewer, E. and J. Jagtiani (2013), How much did banks pay to become too-big-to-fail and to become systemically important?, *Journal of Financial Services Research,* 43**,** 1-35.

Buch, C. M. and L. S. Goldberg (2022), Complexity and riskiness of banking organizations: Evidence from the International Banking Research Network. Elsevier.

Campello, M. (2002), Internal capital markets in financial conglomerates: Evidence from small bank responses to monetary policy, *The Journal of Finance,* 57**,** 2773-805.

Cao, J. and R. E. Juelsrud (2022), Opacity and risk-taking: Evidence from Norway, *Journal of Banking & Finance,* 134**,** 106010.

Carmassi, J. and R. Herring (2016), The corporate complexity of global systemically important banks, *Journal of Financial Services Research,* 49**,** 175-201.

Cetorelli, N. and L. S. Goldberg (2012), Liquidity management of US global banks: Internal capital markets in the great recession, *Journal of International Economics,* 88**,** 299-311.

Cetorelli, N. and L. S. Goldberg (2014), Measures of complexity of global banks, *Economic Policy Review,* 20.

Cetorelli, N., J. Mcandrews and J. Traina (2014), Evolution in bank complexity, *Forthcoming Version of Evolution in Bank Complexity, Economic Policy Review,* 20.

Chakravarthy, B. S. (1986), Measuring strategic performance, *Strategic management journal,* 7**,** 437-58.

Chernobai, A., A. Ozdagli and J. Wang (2021), Business complexity and risk management: Evidence from operational risk events in US bank holding companies, *Journal of monetary economics,* 117**,** 418-40.

Coles, J. L., N. D. Daniel and L. Naveen (2008), Boards: Does one size fit all?, *Journal of Financial Economics,* 87**,** 329-56.

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

Dalton, D. R., C. M. Daily, J. L. Johnson and A. E. Ellstrand (1999), Number of directors and financial performance: A meta-analysis, *Academy of Management journal,* 42**,** 674-86.

Dell'ariccia, G. and R. Marquez (2010), Risk and the corporate structure of banks, *The Journal of Finance,* 65**,** 1075-96.

Demirgüç-Kunt, A. and H. Huizinga (2010), Bank activity and funding strategies: The impact on risk and returns, *Journal of Financial Economics,* 98**,** 626-50.

Deng, S. E. and E. Elyasiani (2008), Geographic Diversification, Bank Holding Company Value, and Risk, *Journal of Money, Credit and Banking,* 40**,** 1217-38.
Deyoung, R., E. Y. Peng and M. Yan (2013), Executive compensation and business policy choices at US commercial banks, *Journal of financial and Quantitative Analysis,* 48**,** 165-96.
Elsas, R., A. Hackethal and M. Holzhäuser (2010), The anatomy of bank diversification, *Journal of Banking & Finance,* 34**,** 1274-87.
Elyasiani, E. and L. Zhang (2015), Bank holding company performance, risk, and "busy" board of directors, *Journal of Banking & Finance,* 60**,** 239-51.
Fahlenbrach, R., A. Low and R. M. Stulz (2017), Do independent director departures predict future bad events?, *The Review of Financial Studies,* 30**,** 2313-58.
Fich, E. M. (2005), Are some outside directors better than others? Evidence from director appointments by Fortune 1000 firms, *The Journal of Business,* 78**,** 1943-72.
Filatotchev, I. and M. Wright (2011), Agency perspectives on corporate governance of multinational enterprises, *Journal of management studies,* 48**,** 471-86.
Flannery, M. J. and C. M. James (1984), The effect of interest rate changes on the common stock returns of financial institutions, *The Journal of Finance,* 39**,** 1141-53.
Flood, M. D., D. Y. Kenett, R. L. Lumsdaine and J. K. Simon (2020), The complexity of bank holding companies: a topological approach, *Journal of Banking & Finance,* 118**,** 105789.
Fosu, S., C. G. Ntim, W. Coffie and V. Murinde (2017), Bank opacity and risk-taking: Evidence from analysts' forecasts, *Journal of Financial Stability,* 33**,** 81-95.
Gandhi, P. and H. Lustig (2015), Size anomalies in US bank stock returns, *The Journal of Finance,* 70**,** 733-68.
Gandhi, P., H. Lustig and A. Plazzi (2020), Equity Is Cheap for Large Financial Institutions, *The Review of Financial Studies,* 33**,** 4231-71.
Gentry, R. J. and W. Shen (2010), The relationship between accounting and market measures of firm financial performance: How strong is it?, *Journal of managerial issues***,** 514-30.
Guay, W. R. (1999), The sensitivity of CEO wealth to equity risk: an analysis of the magnitude and determinants, *Journal of Financial Economics,* 53**,** 43-71.
Guerry, N. and M. Wallmeier (2017), Valuation of diversified banks: New evidence, *Journal of Banking & Finance,* 80**,** 203-14.
Hagendorff, J. (2014), Corporate Governance in Banking. in: Berger, A. N., P. Molyneux and J. O. S. Wilson (eds.) The Oxford handbook of banking. Oxford University Press.
Harimaya, K. and Y. Ozaki (2021), Effects of diversification on bank efficiency: Evidence from Shinkin banks in Japan, *International Review of Economics & Finance,* 71**,** 700-17.
Harris, M. and A. Raviv (2008), A theory of board control and size, *The Review of Financial Studies,* 21**,** 1797-832.
Herring, R. J. and J. Carmassi (2012), The Corporate Structure of International Financial Conglomerates: Complexity and its Implications for Safety and Soundness. in: Berger, A. N., P. Molyneux and J. O. S. Wilson (eds.) The Oxford handbook of banking. Oxford University Press.
Ho, K., E. Wong and E. Tan (2022), Complexity of global banks and the implications for bank risk: Evidence from foreign banks in Hong Kong, *Journal of Banking & Finance,* 134**,** 106034.
Hughes, J. P., W. W. Lang, L. J. Mester, C.-G. Moon and M. S. Pagano (2003), Do bankers sacrifice value to build empires? Managerial incentives, industry consolidation, and financial performance, *Journal of Banking & Finance,* 27**,** 417-47.
Hüpkes, E. H. (2005), Too big to save–towards a functional approach to resolving crises in global financial institutions, *Systemic Financial Crises: Resolving Large Bank Insolvencies***,** 193-216.
Jacewitz, S. and J. Pogach (2018), Deposit rate advantages at the largest banks, *Journal of Financial Services Research,* 53**,** 1-35.
Jensen, M. C. (1993), The modern industrial revolution, exit, and the failure of internal control systems, *The Journal of Finance,* 48**,** 831-80.
Jensen, M. C. and W. H. Meckling (1976), Theory of the firm: Managerial behavior, agency costs and ownership structure, *Journal of Financial Economics,* 3**,** 305-60.
Jones, J. S., W. Y. Lee and T. J. Yeager (2013), Valuation and systemic risk consequences of bank opacity, *Journal of Banking & Finance,* 37**,** 693-706.
Kahn, C. and A. Winton (2004), Moral hazard and optimal subsidiary structure for financial institutions, *The Journal of Finance,* 59**,** 2531-75.
Kim, T., H.-D. Kim and K. Park (2023), Customer concentration and firm risk: The role of outside directors from a major customer, *Journal of Banking & Finance,* 152**,** 106870.
Kostova, T., P. C. Nell and A. K. Hoenen (2018), Understanding Agency Problems in Headquarters-Subsidiary Relationships in Multinational Corporations: A Contextualized Model, *Journal of Management,* 44**,** 2611-37.

Laeven, L. and R. Levine (2007), Is There a Diversification Discount in Financial Conglomerates, *Journal of Financial Economics,* 85**,** 331-67.
Laeven, L. and R. Levine (2009), Bank governance, regulation and risk taking, *Journal of Financial Economics,* 93**,** 259-75.
Lewbel, A. (2012), Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models, *Journal of Business & Economic Statistics,* 30**,** 67-80.
Liu, H., L. Norden and F. Spargoli (2016), Why banks want to be complex. The American Economic Association 2016 Meetings.
Lubatkin, M. and R. E. Shrieves (1986), Towards reconciliation of market performance measures to strategic management research, *Academy of Management Review,* 11**,** 497-512.
Luciano, E. and C. Wihlborg (2018), Financial synergies and systemic risk in the organization of bank affiliates, *Journal of Banking & Finance,* 88**,** 208-24.
Marinelli, G., A. Nobili and F. Palazzo (2022), The multiple dimensions of bank complexity: Effects on credit risk-taking, *Journal of Banking & Finance,* 134**,** 106039.
Martynova, N. and U. Vogel (2022), Banks' complexity-risk nexus and the role of regulation, *Journal of Banking & Finance,* 134**,** 106120.
Mehran, H. and R. M. Stulz (2007), The economics of conflicts of interest in financial institutions, *Journal of Financial Economics,* 85**,** 267-96.
Moreno, D. and T. Takalo (2016), Optimal bank transparency, *Journal of Money, Credit and Banking,* 48**,** 203-31.
Mudambi, R. and P. Navarra (2004), Is knowledge power? Knowledge flows, subsidiary power and rent-seeking within MNCs, *Journal of International Business Studies,* 35**,** 385-406.
Nakano, M. and P. Nguyen (2012), Board Size and Corporate Risk Taking: Further Evidence from Japan, *Corporate Governance: An International Review,* 20**,** 369-87.
O'donnell, S. W. (2000), Managing foreign subsidiaries: agents of headquarters, or an interdependent network?, *Strategic management journal,* 21**,** 525-48.
Parrino, R., A. M. Poteshman and M. S. Weisbach (2005), Measuring investment distortions when risk-averse managers decide whether to undertake risky projects, *Financial Management,* 34**,** 21-60.
Pathan, S. (2009), Strong boards, CEO power and bank risk-taking, *Journal of Banking & Finance,* 33**,** 1340-50.
Raheja, C. G. (2005), Determinants of board size and composition: A theory of corporate boards, *Journal of financial and Quantitative Analysis,* 40**,** 283-306.
Raykov, R. and C. Silva-Buston (2020), Holding company affiliation and bank stability: Evidence from the US banking sector, *Journal of Corporate Finance,* 65**,** 101739.
Sawada, M. (2013), How does the stock market value bank diversification? Empirical evidence from Japanese banks, *Pacific-Basin Finance Journal,* 25**,** 40-61.
Scharfstein, D. S. and J. C. Stein (2000), The dark side of internal capital markets: Divisional rent-seeking and inefficient investment, *The Journal of Finance,* 55**,** 2537-64.
Stein, J. C. (1997), Internal capital markets and the competition for corporate resources, *The Journal of Finance,* 52**,** 111-33.
Strahan, P. E. and J. P. Weston (1998), Small business lending and the changing structure of the banking industry, *Journal of Banking & Finance,* 22**,** 821-45.
Sun, J. and G. Liu (2014), Audit committees' oversight of bank risk-taking, *Journal of Banking & Finance,* 40**,** 376-87.
Tran, D. V., M. K. Hassan, R. Houston and M. R. Rabbani (2022), The impact of bank opacity on bank risk-taking behavior, *Journal of Corporate Accounting & Finance,* 33**,** 88-101.
Uchida, H. and G. F. Udell (2019), Banking in Japan: A Post-global Financial Crisis Perspective. in: Berger, A. N., P. Molyneux and J. O. S. Wilson (eds.) The Oxford handbook of banking. Oxford University Press.
Ueda, K. and B. W. Di Mauro (2013), Quantifying structural subsidy values for systemically important financial institutions, *Journal of Banking & Finance,* 37**,** 3830-42.
Weisbach, M. S. (1988), Outside directors and CEO turnover, *Journal of Financial Economics,* 20**,** 431-60.
Yildirim, C. and G. Efthyvoulou (2018), Bank value and geographic diversification: regional vs global, *Journal of Financial Stability,* 36**,** 225-45.
Zheng, Y. (2020), Does bank opacity affect lending?, *Journal of Banking & Finance,* 119**,** 105900.
Zouaoui, H. and F. Zoghlami (2023), What do we know about the impact of income diversification on bank performance? A systematic literature review, *Journal of Banking Regulation,* 24**,** 286-309.

Chapter 5 Conclusion

In this dissertation, I first investigated the impact of diversification on Japanese bank performance. Subsequently, I explored one channel associated with diversification benefits. Lastly, I extended the research to a similar topic, bank complexity, and examined the relationship between complexity, governance, and bank performance. The main findings of the three empirical studies are summarized as follows:

Chapter 2 examined the impact of diversification on bank performance, measured by profitability and risk. The results reveal a positive relationship between diversification and ROA, coupled with a negative association with net interest margins. This suggests that while diversification can enhance overall profitability, it comes at the expense of reduced profitability from traditional business activities, indicating a loss leader function within interest-generating businesses. Moreover, asset diversification is found to reduce bank risk, with no significant impact observed for income diversification. Additionally, I also found several nonlinear relations. Although some can be explained by the inclusion of online banks that have a different business model than traditional commercial banks, the remaining can still be significant even when excluding the influence of online banks. This is consistent with what I observe when considering the impacts of bank types on diversification effects, implying diversification effects vary across different banks. For example, banks with higher income diversification, such as city banks, exhibit lower marginal effects, while the effects are more pronounced for second regional banks relying more on traditional lending business. In additional analysis, I found that different non-interest businesses, such as fees and trading, have different impacts on bank performance, and income and asset diversification exhibit opposing effects on risk during crisis periods.

Chapter 3 estimated economies of scope in the Japanese banking industry. Instead of estimating scope economies at the industry level as most previous studies have done, I calculated two alternative measures for scope economies for each bank in each year: within-sample scope economies and economies of diversification. These two measures relax the assumption of full specialization and allow for partial production in calculating economies of scope, which is more realistic. The results show that most Japanese banks exhibit positive within-sample scope economies, with a clear upward trend in the average value. When considering the difference across banks of different sizes, I found that small banks initially tend to have relatively higher estimators, while this difference has narrowed considerably in recent years. Similarly, I also found that economies of diversification are positive for Japanese banks,

which can be attributed to positive complementarity and scale effects. Moreover, I investigated the relationship between bank diversification and the estimated scope economies. The results suggest a negative impact of diversification on scope economies, implying that diversified banks benefit less from scope economies. This may explain why the marginal diversification effect is lower for more diversified banks in Chapter 2.

Chapter 4 examined the relationship between bank complexity, governance, and performance. Bank complexity is measured based on the number of subsidiaries in terms of organizational, business, and geographic dimensions. In assessing bank governance, I focused on the board shareholding and the composition of the board. The results show that only business complexity is found to be positively associated with bank market value, and there is no strong and consistent evidence for a risk-decline effect. Specifically, complexity tends to negatively impact market-based risk measures but turns positive for insolvency risk. When considering the impact of bank governance, it indicates that higher board shareholding, larger boards, and fewer independent directors can reduce bank risk-taking behaviors, but have no significant effects on market value. Although better governance is expected to be more effective in mitigating the adverse effects of complexity in complex banks, the results suggest a limited role for bank governance in moderating the impact of complexity on bank performance, particularly in risk. Conversely, some results suggest that higher board shareholding and large boards may exacerbate the adverse effects of complexity. Furthermore, the positive effects of complexity can be explained by diversification benefits and lower funding costs, while the incentive for risk-taking may be driven by bank opacity. Subsample analysis for banks of different sizes indicates that small banks gain little benefit and face more risk from a complexity strategy, whereas large banks are riskier when they become more complex in business.

Overall, this work provides evidence that Japanese banks can benefit from business expansion both from diversification and complexity perspectives. These results strongly contradict diversification discounts found in the U.S. or other markets and are consistent with findings in Sawada (2013). In the channel analysis, positive economies of scope and economies of diversification, a cost-saving effect through joint production, are found to be effective, which explains why banks expanding into new businesses can improve bank profitability and market value. However, our results also indicate a negative relationship between scope economies and diversification. This implies that highly diversified banks may not experience the expected increase in economies of scope. Conversely, the decrease in economies of scope discourages banks from further diversification. On the other hand, while governance affects bank

performance, its impact on the complexity effect is limited. This suggests that governance may not be effective in mitigating the agency costs associated with complexity, or that agency problem may not play a dominant role in the net effect in Japan. As for risk, evidence is mixed as opponent effects are observed under different settings. Diversifying assets and entering new industries can mitigate the volatility of profitability or stock returns, while the impact on insolvency risk may be insignificant or even increase when banks diversify income sources or become more complex. What is more, the effects of diversification or complexity vary based on factors such as bank size, type, and governance, emphasizing the need to consider heterogeneity among banks when evaluating diversification and complexity strategies.

While this study provides some insights into bank business expansion, there are several avenues for further exploration. First, bank business expansion can be studied from a more specific perspective. The current analysis tends to simplify the classification of non-interest businesses or subsidiaries, potentially overlooking changes in regulations or trends that need further investigation. For instance, regional banks are allowed to engage in regional commerce business to support the revitalization of regional economies. I believe that research on such topics can generate more insights into the practice of bank business expansion in Japan. Second, the identification strategy problem should be more addressed. While this work has adopted several methods to address the endogeneity of key independent variables, it still suffers from concerns about the validity of these tests, such as the selection of IVs. The reliability of results could be strengthened by employing more generalized research methodologies. Lastly, it calls for more in-depth mechanism studies. In Chapters 3 and 4, I have examined two channels of diversification, and it will be more helpful to further study other channels, such as the internal capital market and other agency costs. Additionally, this work has found some interesting results, such as the negative relationship between diversification and scope economies or the multiple functions of bank governance in complex banks. Unfortunately, due to limitations in capacity and space, these findings are not extensively explained in this work. I believe that more mechanism studies would help to understand these issues.