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Effect of diversity on Chinese bank risk

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Ph.D. in Finance

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Resumo

Esta tese, composta por três artigos, centra-se no efeito da diversidade sobre o risco dos bancos comerciais chineses.

O primeiro artigo investiga a relação entre risco e diversidade a partir da diversidade empresarial no sector bancário chinês. As amostras abrangem os bancos chineses de acções e os bancos comerciais urbanos durante os períodos de 2009 a 2020. As principais conclusões são as seguintes: os resultados de base mostram que a diversidade de activos é consistente com a hipótese do risco de agência, enquanto a diversidade de rendimentos é consistente com a hipótese da diversificação. Os bancos cotados são mais sensíveis à diversidade de empresas do que os bancos não cotados, o que é coerente com a hipótese de agência. A diversidade empresarial para os bancos não "TBTF" tem um ligeiro efeito negativo no risco bancário. Construímos ainda uma diversidade geográfica para interagir com a diversidade de activos e de rendimentos, o resultado mostra que a diversidade geográfica pode inibir o impacto da diversidade de rendimentos na redução do risco bancário. Após a adição de variáveis instrumentais, um teste de robustez mostra um efeito positivo no lnZscore. As variáveis instrumentais sugerem que os bancos mais próximos do centro económico da China têm maior probabilidade de prosseguir a expansão do negócio.

O segundo artigo avalia o impacto da diversidade do conselho de administração no risco bancário no sector bancário chinês. As amostras abrangem todos os bancos comerciais chineses cotados na Bolsa de Valores de Xangai, na Bolsa de Valores de Shenzhen e na Bolsa de Valores de Hong Kong durante os períodos de 2006 a 2021. A nossa principal conclusão é que o risco bancário pode ser menor se houver um conselho de administração mais diversificado (em particular nos pequenos bancos) ou um conselho de supervisão mais diversificado (em particular nos grandes bancos); isto é consistente com a hipótese de agência. Na análise de regressão quantílica, verificamos que os factores demográficos (mulheres e idade) têm uma relação em forma de U invertido, enquanto os factores cognitivos (habilitações literárias e conhecimentos financeiros) têm uma relação em forma de U. Além disso, também quantificamos o efeito do governo, nomeadamente a percentagem de membros do conselho de administração designados pelo governo ou cujo anterior emprego foi num departamento governamental, mas concluímos que tem pouco impacto no risco bancário. Por último, utilizamos a fração de membros do conselho de administração que trabalham noutras empresas como variável instrumental e os resultados são coerentes com as nossas conclusões.

O terceiro artigo investiga a relação entre tecnologia e risco bancário, utilizando as amostras de bancos comerciais chineses de 2007 a 2020. Medimos o rácio de desenvolvimento tecnológico utilizando o modelo de fronteira estocástica como principal variável independente, e o logaritmo do Z-score como variável dependente. Apresentamos e testamos a hipótese da eficiência e a hipótese da agência. Os resultados de base são consistentes com a predominância da hipótese da agência, em que os gestores de topo procuram recompensas pessoais que compensem os benefícios do progresso tecnológico. No entanto, os resultados dos bancos com capacidade tecnológica abaixo da média do sector, bem como dos bancos com capacidade tecnológica de topo, são consistentes com o predomínio da hipótese da eficiência - a capacidade tecnológica melhora a eficiência na gestão do risco. O desenvolvimento tecnológico tem um efeito negativo tanto nos bancos públicos como nos bancos comerciais urbanos, e o efeito nos bancos públicos é cerca de 4 vezes superior ao dos bancos comerciais urbanos. Nos testes de robustez, concluímos ainda que o nível de risco anterior dos bancos pode facilitar uma melhor gestão do risco. Ao mesmo tempo, o nível de tecnologia anterior dos bancos continuará a facilitar a sua inovação tecnológica e a avaliação dos riscos. Além disso, as FinTech externas são um fator importante que, em certa medida, agravará o risco bancário. Por um lado, quando a FinTech coopera com os bancos na ausência de regulamentação suficiente, aumenta a exposição ao risco bancário, mas, por outro lado, divide parte da atividade do banco.

Classificação JEL: G21; G28; L25; G30

Palavra-chave: Risco bancário; Diversidade corporativa; Diversidade de conselho de administração; Risco de agência; Tecnologia

Abstract

This thesis, consisting of three papers, focuses on the effect of diversity on Chinese commercial bank risk.

The first paper investigates the relationship between risk and diversity from corporate diversity in Chinese banking industry. The samples cover the Chinese joint-stock banks and city commercial banks over the periods from 2009 to 2020. The main findings are as follows: the baseline results show that asset diversity is consistent with the agency risk hypothesis, while income diversity is consistent with the diversification hypothesis. Listed banks are more sensitive to corporate diversity relative to non-listed banks, which is consistent with the agency hypothesis. Corporate diversity for non-“TBTF” banks has a slight negative effect on bank risk. We further construct a geographical diversity to interact with asset and income diversity, the result shows that geographical diversity may inhibit the impact of income diversity on reducing bank risk. After adding instrumental variables, a robustness test shows a positive effect on lnZscore. Instrumental variables suggest that banks closer to the economic center in China are more likely to pursue business expansion.

The second paper evaluates the impact of board diversity on bank risk in Chinese banking industry. The samples cover the all listed Chinese commercial banks in Shanghai Stock Exchange, Shenzhen Stock Exchange and Hong Kong Stock Exchange over the periods from 2006 to 2021. Our main finding is that bank risk can be lower if there is a more diversified board (in particular in small banks) or a more diversified supervisory board (in particular in large banks); this is consistent with agency hypothesis. In quantile regression analysis, we find demographic factors (female and age) have an inverted U-shaped relation, while cognitive factors (education background and financial expertise) have a U-shaped relation. Furthermore, we also quantify the government effect, namely the percentage of board members assigned by the government or whose previous job was in a government department but find it has little impact on bank risk. Finally, we use the fraction of board members who are sitting in other firms as instrumental variable, the results are consistent with our findings.

The third paper investigates the relationship between technology and bank risk, using the samples of Chinese commercial banks from 2007 to 2020. We measure technology development ratio using stochastic frontier model as the main independent variable, and the logarithm of Z-score as the dependent variable. We offer and test efficiency hypothesis and agency hypothesis. The baseline results are consistent with a dominance of the agency hypothesis where senior managers seek personal rewards that will offset the benefits of technological progress. However, the results of banks with below industry average technological capability as well as banks with top technological capability are consistent with a dominance of the efficiency hypothesis — technological capability improves efficiency in managing risk. Technology development has a negative effect on both state-owned banks and city commercial banks, and the effect on state-owned banks is about 4 times larger than that on city commercial banks. In robustness tests, we further find banks' past risk level can facilitate better risk management. At the same time, the banks' past level of technology will continue to facilitate its technological innovation and risk assessment. Moreover, external FinTech is an important factor that will to some extent exacerbate bank risk. On one hand, when FinTech cooperates with banks in the absence of sufficient regulation, it increases bank risk exposure but, on the other, it divides part of the bank's business.

JEL Classification: G21; G28; L25; G30

Keywords: Bank risk; Corporate diversity; Board diversity; Agency risk; Technology

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CHAPTER 1

Introduction

Since China's reform and opening up, the Chinese economy has become more and more open. The integration of the global economic market and the development of liberalization have brought good opportunities for the financial industry while at the same time posing important challenges to the international financial market, with the uncertainty and riskiness of the market gradually increasing. The Chinese banking industry has gone through a period of market exploration, market reform and international reform. The formation of bank risk is closely related to the economic environment it faces. As the second largest economy in the world, China has a strong demand for loans and financing. With the rapid rise of non-bank financial structures, it has impacted on the existing market share and business of banks. At the same time, various financial institutions are constantly developing new financial instruments, such as derivatives, to attract customers and expand their market share in order to maintain their existing profit levels and grasp the competitive market initiative. Compared with other financial institutions, the competitive advantage of banks still lies in their outstanding risk management and ability to deal with complex financial issues. In the face of increasingly fierce financial competition, banks still act as the core identity of financial intermediaries to ensure the match between financial supply and real economy demand. However, banks are beginning to face new risks arising from market transformation, such as business risk, market risk, operational risk and liquidity risk.

Nowadays, with the sweeping wave of digitalization and FinTech factor-driven, the digital and ecological transformation of banks has become an inevitable trend in China's banking industry. The development and innovation of IT is also a double-edged sword for banks. On the one hand, it can effectively reduce bank costs and improve work efficiency. On the other hand, information technology may be accompanied by human operational risks, data risks and platform risks. Therefore, in the changing technological environment, banks need to constantly recognize risks, scientifically avoid risks and manage risks.

In recent years, the China Banking and Insurance Regulatory Commission (CBIRC) has called for greater efforts to dispose of non-performing assets, reduce banks' non-performing asset ratios and improve their ability to withstand risks. The bank risk, in addition to changes in the market environment technological environment and regulatory requirements, faces many factors of its own, for example, whether adding a new branch would be beyond the scope of its risk management? Can the board structure reduce its risk from a diversified perspective? Does the bank's own technological innovation expand the bank's level of risk tolerance? Based on the above background, this thesis will explore the impact of diversification on the risk of Chinese commercial banks from a diversification perspective.

In studying the effect of geographical diversity and product diversity on bank risk, many prior studies have used portfolio theory hypothesis and agency theory hypothesis, which are used to explain our empirical results in Chapter 2 as well (Goetz, Laeven, Levine, 2016; Zamore, Beisland, Mersland, 2019; Deng, Elyasiani, 2008; Berger et al., 2005; Wang, Lin, 2021). Under agency hypothesis, bank managers may have opportunities to extract private benefits through expanding geographically and using aggressive business strategies to achieve higher bonus, as distance and remote can hinder the management and monitoring from headquarters, which may lead to the conflict of interest with shareholders and owners. Under portfolio hypothesis, in some research, it is also written as diversification hypothesis, a bank has a diversified portfolio may have less risk. “Don’t put all eggs in one basket”, banks can, to some extent, have a greater risk buffer by diversifying income sources and investing in diversified assets, thus increasing their risk taking. Besides, there are also other hypotheses discussed in the research related to geographical diversity and product diversity. Berger et al., (2015) provide market risk hypothesis. Under this hypothesis, it suggests that because of the different conditions in different markets and other market-specific factors, such as exchange rate, regulatory requirements, international banks may have higher risk and face to greater risk on foreign asset. In this case, Berger et al., (2015) adopt foreign asset ratio as the main independent variable to estimate the effect of internalization on bank risk. They use the data of all banks in U.S. from 1980 to 2010 and OLS method, and find that internalization has a negative relation to bank risk, which means a dominance of market risk hypothesis. Goetz, Laeven and Levine (2016) develop cost efficiencies hypothesis. Under this hypothesis, cost efficiencies could enhance stability. A bank may benefit from too big or interconnected to fail because of the implicit or explicit government guarantees. They develop geographic diversity as the main variable by measuring 1-the Herfindahl-Hirschman index of a bank deposits across branches, and use OLS method. The results are consistent with the cost efficiencies hypothesis — geographic expansion lowers bank risk.

In terms of board diversity, there are many theories and hypotheses. The three most common theories are agency theory, resource dependence theory and human capital theory (Talaveraa, Yin, Zhang, 2018; Arioglu, 2021; Jebrana, Chen, Zhang, 2020; Abou-El-Sood, 2021). These three theories correspond to the hypotheses are as follows: under agency hypothesis, the board is an important bank internal mechanism to mitigate the conflicts of managers and shareholders. Board diversity can increase board independence and efficiency from different perspectives. Under resource dependence hypothesis, the business and operation of a bank is dependent on the external environment, and a diverse board could provide valuable network and resources. Under human capital hypothesis, board members come from different background of education and monitor different skills, which brings creativity and innovation to the boardroom. Based on these hypotheses, Talaveraa, Yin, Zhang (2018) employ board age diversity as main variable and use OLS to examine the effects on bank profitability and risk, and they find board age diversity is negatively associated with bank profitability but insignificant on bank risk. There are also other alternative theory and hypotheses. For example, Papadimitria, Pasiouras, Tasiou,, Ventouri (2020) use upper echelons theory — the strategies and performance are partial decided by the background characteristics of board. Using the dataset from 39 countries, they construct a Leadership Education Index that reflects the educational level of board members to estimate the influence of the educational attainment of board members on its credit rating. Their findings show that board with higher educational level is more likely to receive a better credit rating. Both Khan, Fraz, Hassan, Abedifar (2020) and Bernile, Bhagwat, Yonker (2018) adopt social psychology hypothesis, which suggests that a diverse board moderate group decisions. Boards with high homogeneity tend to produce more idiosyncratic decisions because they are subject to less oversight. In the research of Bernile, Bhagwat, Yonker (2018), for example, they construct a multidimensional board diversity by using the data of U.S. corporates to estimate the effect of diversity in the board of directors on corporate risk, and find that a diverse board may adopt more persistent and less risky financial policies, which results in lower risk. Moreover, Arioglu (2021) develops other hypotheses, such as managerial signaling hypothesis, market learning hypothesis and social responsibility hypothesis, when he discusses the topic of board age and value diversity on bank profitability and risk. Managerial signaling hypothesis suggests younger directors are more like to show their worth to the market and adopt more aggressive strategies and risk taking, while market learning hypothesis is opposite, younger directors are more risk averse and conservative to make decision. Social responsibility hypothesis suggests that younger directors may be more sensitive in terms of ethical and environmental issues. To address and verify these hypotheses, Arioglu (2021) use the data of listed companies at Borsa Istanbul between 2009 and 2017 to regress OLS of board diversity on bank profitability and risk. The findings support the managerial signaling hypothesis.

In terms of technology, there are not too many literatures that study in bank risk. Berger et al., (2005) develop efficiency hypothesis and hubris hypothesis. Under efficiency hypothesis, large banks are benefit more from technological progress, as technological progress brings scale economies over time. Managers and staffs in the banks with advanced informational technology can work more efficiently and conveniently across departments, branches and countries, which results in higher performance and lower risk. Under hubris hypothesis, managers in large banks prefer to engage in mergers and acquisitions to increase size and geographic spread in order to reward higher personal bonus. They separate the data over the period from 1982 to 2020 into four groups, large banks and small banks before and after 1990s, and use OLS method to estimate on bank performance. Their empirical results show dominance of the efficiency hypothesis over the hubris hypothesis.

Base on the background, theories and hypotheses, this PhD thesis addresses the main research question about the effect of diversity on Chinese commercial bank risk in three separate and self-contained papers.

This thesis proceeds as follows. Chapter 2 presents the first paper, I estimate the effect of diversity (geographical diversity and product diversity) on bank risk. Chapter 3 presents the second paper, I try to figure out the relationship between board diversity and bank risk. Chapter 4 presents the third paper, I investigate the effect of technology on bank risk. Finally, Chapter 5 concludes.

CHAPTER 2

Corporate Diversity and Bank Risk

Abstract: This paper contributes to the investigation into the relationship between risk and corporate diversity in the Chinese banking industry. We use asset diversity and income diversity as a measure of corporate diversity. The samples cover the Chinese joint-stock banks and city commercial banks over the period from 2009 to 2020. The main findings are as follows: the baseline results show that asset diversity is consistent with the agency risk hypothesis, while income diversity is consistent with the diversification hypothesis. Listed banks are more sensitive to corporate diversity relative to non-listed banks, which is consistent with the agency hypothesis; corporate diversity increase listed bank risk as managers can pursue aggressive expansion in pursuit of their own rewards at the expense of shareholders, leading to greater risk exposure. Corporate diversity for non-"TBTF" banks has a slight negative effect on bank risk. We further construct a geographical diversity to interact with asset and income diversity, the result shows that geographical diversity may inhibit the impact of income diversity on reducing bank risk. After adding instrumental variables, a robustness test shows a positive effect on lnZscore. Instrumental variables suggest that banks closer to the economic center in China are more likely to pursue business expansion.

JEL Classification: G21; G28; L25

Keywords: Risk; Geographical diversity; Product diversity; Agency risk; Diversification

2.1. Introduction

The continuous development of economic globalization has led to greater interest in financial diversity, and the development of diverse strategies by commercial banks. Diversified corporate operations are mainly reflected in corporate diversity, which is a principal strategy used by banks to expand their business. We address the impact of corporate diversity on bank risk. Corporate diversity plays a part in alleviating default risk in banking industry (Diamond, 1984; DeYound and Torna, 2013; Shim, 2013). Commercial banks not only confine their business to a certain region but have also started to lay out a national and global market. Although much research finds a connection between diversity and bank risk, the issue calls for further attention.

Increasing competition and changing market conditions have forced banks to shift from traditional lending business to non-interest activities. Banks diversify assets portfolios to increase their performance (Meslier et al., 2014). In recent years, China's financial market has been expanding and opening up to the outside world. Chinese commercial banks have successively launched a number of non-traditional banking businesses such as letters of credit, acceptance and discounting of commercial paper, foreign exchange trading, and underwritings services. Since 2019 Chinese commercial banks have started to set up bank wealth management subsidiaries specializing in investment business.

Affected by the economic globalization, China has gradually deregulated banking business since 2004, the behavior of Chinese commercial banks is still vulnerable to policy influence. The third draft amendment to the Commercial Bank Law was published in October 2020, which broadened the scope of banking business operations. Three new items were added: derivatives trading business, precious metals trading business, and offshore banking business. At the same time, the draft also emphasizes risk management, risk classification and appropriateness management, and for the first time clarifies the handling of restructuring, receivership, bankruptcy.

Previous literatures focus on the impact of diversity on bank risk and the results are mixed (DeYoung, Torna, 2013; Wang, Lin, 2021; Shim, 2013; Baele et al., 2016; Yang et al., 2020; Stiroh, 2004; Schmid, Walter, 2009; Zhang et al., 2020). One possible explanation is that different researchers measure diversity in different ways. Another possible explanation is that the sample for the study is drawn from different countries, which also have different regulatory and policy requirements for banks, making it possible for diversification to promote or inhibit bank risk. The over-riding focus on the U.S. and European banking sector in the diversity literature is a major limitation. This paper aims to investigate the relationship between corporate diversity and bank risk in Chinese market.

Diversity may lead to both benefits and costs. The traditional arguments for benefits from corporate diversity are based on lower risks and greater economies of scope. Given that noninterest income is different from traditional interest income in terms of the revenue model, increased noninterest income will reduce the risk of failure (DeYound and Torna, 2013). Economies of scale enterprises are mainly concentrated in infrastructure, mass consumption and emerging enterprises, which often have government support and low risk characteristics; banks' participation in these projects through lending can increase their profit with low risks. On the contrary, diversity may be costly due to agency problems. Agency problems will increase of the inconsistent incentives of bank managers and shareholders. Bank managers may choose diversify if expansion enhances bank performance and they may extract more benefits from expansion activities.

In this paper, we investigate the effect of diversity on bank risk in China from two dimensions: asset diversity and income diversity. There are also distinct measures of risks: First, Z-score is defined as the sum of a bank's mean ROA and mean Capitalization Ratio (equity capital/ total asset) divided by Stdv. ROA (standard deviation of ROA). Second, the non-performing loan rate (NPL rate) is defined as the proportion of a loan portfolio that is in arrears for longer than 90 days. Third, non-performing provision coverage (NPL provision coverage) is defined as the proportion of the non-performing loans covered by provisions. Moreover, in robustness test, we use Stdv. ROA and Volatility as the risks. We further construct a moderating variable geographical diversity to interact with asset diversity and income diversity to see if it moderates the impact of these variables on bank risk. We also employ instrumental variables (IV) to estimate whether the distance from the bank headquarters to the economic center and also the policies related to geographic expansion are endogenous variables of corporate diversity. In fact, we found this to be the case.

Our findings from the simple OLS model show that the asset diversity results are consistent with the agency risk hypothesis, and income diversity results are consistent with the diversification hypothesis. The results for listed banks are consistent with agency risk hypothesis. Listed banks are more sensitive to corporate diversity, leading to increased risk in these banks. Bank managers in listed banks adopt more aggressive business strategies and geographic expansion strategies in order to achieve a higher bonus relative to non-listed banks. It is difficult for bank managers to manage and control many branches efficiently at the same time, which may lead to higher costs and higher potential risk. In addition, an aggressive business strategy can also be seen in the risk preference portfolio, which is more diverse in listed than non-listed banks and includes loans, derivatives, precious metals, etc., leading to greater risk exposure. Moreover, the moderating variable geographical diversity weakly affects the negative relationship between asset diversity and bank risk. Finally, we employ the IV variable and 2SLS model to estimate the impact of diversity on risks; the results confirm that income diversity may lower bank risk.

The rest of the paper is organized as follows. Section 2 sets out the background to the Chinese banking industry. Section 3 presents the data and variables. Section 4 describes the method, results and subsequent discussion. Section 5 reports the robustness tests. Section 6 concludes.

2.2. Literature review and hypotheses

Existing studies that investigate in Chinese commercial banks mainly focus on the relationship between bank risk, efficiency and profitability (Tan, Floros, 2013; Tan, Floros, Anchor, 2017), but less on diversity (Zhang et al., 2020; Li et al., 2021). For instance, Zhang et al. (2020) investigate the effect of corporate diversity on bank credit risks. Li et al. (2021) investigate the impact of revenue diversity on bank risk during the COVID-19 pandemic. In addition, there is little literature discussing whether policy restrictions on diversity affect Chinese commercial bank risk. In fact, the behavior of China's banking sector is vulnerable to policy influence.

The main variables of corporate diversity in previous studies are asset diversity, income diversity (Laeven, Levine, 2007; Laeven, Levine, 2009) and revenue diversity (Hou, et al., 2018). Asset diversity is calculated as one minus the difference between net loans and other earning assets as a percentage of total earning assets. Similarly, income diversity is calculated as one minus the difference between net interest income and other operating income as a percentage of total operating income (Laeven, Levine, 2007; Laeven, Levine, 2009). Hou et al., (2018) measure diversity by using an alternative method. They consider the structure of income statements, which is the share of net interest income generated by traditional activities and non-interest income generated by non-traditional activities.

Empirically, previous studies show mixed results. Most studies provide evidence to show that income diversity can reduce risk. For instance, DeYoung and Torna (2013) examine the U.S. commercial banks during the financial crisis and find that while banks with pure fee-based noninterest activities are less likely to go bankrupt, those with asset-based noninterest activities are more likely to do so. Wang and Lin (2021) employ a sample of commercial banks in 14 Asia Pacific economies from 2011 to 2016 and find that the greater the banks' income diversity, the less risky their burden becomes. Shim (2013) argues that U.S. bank holding companies with a diversified operating revenue have a lower insolvency risk. Baele et al. (2006) employ data on commercial banks in 17 European countries from 1989 to 2004 and find that the relationship between diversity and bank-specific risk is predominantly downward-sloping; in other words, most banks can reduce their risk by diversifying their revenues under the optimal threshold. Yang et al. (2020) examine the effects of the diversity of U.S. commercial bank revenue on systemic risk and argue that the association between bank diversity and an increase in systemic risk is more significant in larger- and medium-sized banks.

However, there are also doubts as to whether noninterest income not only stabilizes revenue and profitability but also reduces risk. Stiroh (2004) examines the data from the aggregate level and bank level. He finds that noninterest income is more volatile than net interest income, and greater reliance on noninterest income leads to higher risk and lower risk-adjusted profits. Schmid and Walter (2009) support this argument and note that diversity lead to a discount among financial intermediaries and the impact of functional scope is predominantly value-destroying.

Based on the mixed results from previous studies, diversity may lead to both benefits and costs. Thus, we develop two hypotheses on the impact of corporate diversity on bank risk. The diversification hypothesis suggests that banks may have lower bank risk because they diversify their assets and income (Laeven and Levine, 2007). On the one hand, banks increase the number of branches to expand their business coverage and achieve revenue growth and risk reduction with scale effect (Berger et al. 2015; Goetz, Laeven, Levine, 2016). On the other hand, banks can effectively maintain their stable revenue and reduce risks by diversifying their business model (Laeven and Levine, 2007).

The alternative agency risk hypothesis suggests that diversity may intensify agency problems between bank insiders and small shareholders (Laeven and Levine, 2007). Banks reward their managers annually by evaluating their performance, and managers may expand financial activities with aggressive strategies to meet performance targets; this may incur increased risk to the bank and harm shareholders' interests.

2.3. Data and variables

2.3.1. Sample context

China's banking industry is different from that of the United States. In the United States, the Federal Reserve is at the core, commercial banks are the main body and there is a financial market-oriented banking system. In contrast, the central bank is at the core of China's banking industry and the four major banks are the main body, but there are also urban commercial and agricultural commercial banks across small cities and urban developments. China began to build a socialist banking system with special characteristics following its reform and opening up in 1978. Wang (2019) divides this period of development into three phases as follows:

The first stage was the 14-year period from 1979 to 1992, when the Chinese banking industry explored market-oriented development. More specifically, the banking industry went through a period of recovery between 1979 and 1984; the banking system was established with the People's Bank of China as the central bank and four state-owned banks, namely, Industrial and Commercial Bank of China, Agricultural Bank of China, Bank of China and China Construction Bank . Over the next 8 years from 1985 to 1992, the banking industry expanded rapidly. China established joint-stock banks and strengthened banking supervision, manifested by improved and greater business scope.

The second stage was the 10-year period from 1992 to 2001, when the market-oriented reform of China's banking system took place. In this phase, the reform and development of China's banking industry was mainly demonstrated by the following. First, banks separated commercial business from policy business and three policy banks were established, namely the China Development Bank, the State Export-Import Bank and the China Agricultural Development Bank, , so that other banks could focus on developing commercial business. Second, the banking industry was legalized. After 1995, the People's Bank of China Law, the Commercial Bank Law, and a series of other financial laws were promulgated to regulate the rights and obligations of commercial banks as well as the scope of their business. Third, the interbank market was established and the planned management of credit scale was abolished, leading to the rapid development of interbank bond trading and bond repurchases and the removal of controls on the size of loans from the big-four banks. The People's Bank of China started to pay more attention to the use of monetary policy for regulation and control. Fourth, a market-based interest rate was launched, and the People's Bank of China liberalized the interbank lending rate. In addition, according to the unified arrangement of the State Council, four major asset management companies were established, namely China Huarong, Cinda, China Orient and China Great Wall, to deal with the non-performing assets divested from banks.

The third stage was the 15-year period from 2002 to 2017: the internationalization stage. In this phase, the main reforms and developments in China's banking industry were: the wholly state-owned commercial banks became state-controlled commercial banks through listing in the Shanghai and Hong Kong stock exchange. The China Banking Regulatory Commission was established in 2003 to strengthen banking supervision. The banking industry fulfilled its WTO accession commitments and the pace of the internationalization of Chinese banks accelerated. Private banks and city commercial banks were developing rapidly. A macro-prudential assessment system was established, which actively prevented and controlled the financial risks. Internet finance was regulated and standardized, while China further expanded its financial opening to the outside world.

2.3.2. Sample banks

Based on the List of Banking Financial Institution Legal Persons (China Banking and Insurance Regulatory Commission, 2021), our dataset covers 135 banks, including state-owned commercial banks, joint equity commercial banks and city commercial banks as our samples. We exclude 1 city commercial bank that was established less than 2 years and 12 city commercial banks whose annual reports were not available. We also exclude rural commercial banks because most of them have a single-structured business and are highly regional in nature, concentrating on serving people in their local areas, which is not suitable for diversity research. Besides, financial disclosure of rural commercial banks is incomplete and much information is difficult to obtain. Our dataset is an unbalanced panel sample and we acquire bank data from annual reports and social responsibility reports of each bank covering the period 2007-2020. We next remove the financial data of the first two years in each bank, because we adopt the rolling window of 3 years to calculate standard deviation of return on asset (ROA) and return on equity (ROE) (Meslier, et al., 2016), therefore, there is no data available of the standard deviation of ROA and ROE of each bank in the first two years, leaving 1255 observations. We further refine our sample by excluding observations without the data of the number of branches or agencies, as well as the data of non-Performing Loan Provision Coverage Ratio (NPL provision coverage Coverage). These screens leave us with a final sample of 1183 observations over the entire sample period.

2.3.3. Variables

2.3.3.1. Measures of risk

We construct three variables to estimate risks. First, as many studies did, we measure *Z-score*, with larger values indicating lower overall bank risk as risks (Beltratti and Stulz, 2012; Berger, et al., 2015; Boyd and Runkle, 1993; Houston, et al., 2010; Laeven and Levine, 2009; Meslier, et al., 2016). In our analysis, we first computer *Stdv. ROA* (the volatility of ROA) by using the rolling window of 3 years, namely the current year and two previous years, following a methodology of Meslier, et al. (2016). We then calculate the logarithm of *Z-score* as the sum of a bank's mean *ROA* and mean *Capitalization Ratio* (equity capital/ total asset) divided by *Stdv. ROA*. Second, following Zamore, Beisland and Mersland (2019), we use non-performing loan rate (*NPL rate*) as risks, defined as the proportion of a loan portfolio that is in arrears for longer than 90 days. Third, we employ non-performing provision coverage (*NPL provision coverage*), defined as the portion of the non-performing loans covered by provisions. It shows to what extent the bank has already recognised losses it expects from non-performing loans. In order to match the data better, we use the raw data of *NPL provision coverage* divide 1,000. Both *NPL rate* and *NPL provision coverage* could be found in the annual report and credit rating report. Besides, we also use the volatility of *ROA* as the alternative measure for bank risk in order to a robustness check.

2.3.3.2. Measures of diversity

One way to capture the corporate diversity in previous literature is to consider asset diversity and income diversity. We follow Laeven and Levine (2007) to construct two variables: asset diversity and income diversity as follows:

$$Div_{Asset} = 1 - |(net\ loans - other\ earning\ assets)/total\ earning\ assets \quad (2.1)$$

where other earning assets include securities and investments. Asset diversity takes values between 0 and 1, the higher values, the greater diversity.

$$Div_{Income} = 1 - |(net\ interest\ income - other\ operating\ income)/ total\ operating\ income| \quad (2.2)$$

where other operating income includes net fee income, net commission income, net trading income and other income. Income diversity takes values between 0 and 1, the higher values, the greater diversity.

2.3.3.3. Control variables

Below we set out our control variables.

Size. Many studies show that bank size is an important determinant of diversity. Larger banks are more diversified and have a greater capacity to absorb risk than smaller banks (Gulamhussen et al., 2014; Berger, Bouwman, Kick, and Schaeck, 2014). Bank size could be correlated with branches and asset diversity. Additional branch could increase bank size and larger banks are more diversified in the asset types. Hence, it makes sense to control bank size in this studies. Following previous studies, we measure as the log of total assets (Berger, et al. 2015; Goetz, Laeven, Levine, 2016; Deng and Elyasiani, 2008).

Listed. Previous studies show that publicly traded banks may be more sensitive to the capital markets, and they are more informationally transparent (Berger, et al. 2015; Barry, Lepetit, and Tarazi, 2011). We follow Berger, et al. (2015) to construct Listed as a dummy variable that take value of 1 if a bank is publicly tradable, and 0 otherwise.

Operating income. If bank's operating income continues to grow steadily and the bank will have sufficient cash flow to develop new businesses or establish new branches to generate more revenue. Hence, it makes sense to control operating income as the log of total operating income.

ROA. It indicates how profitable a bank is in relation to its total asset. It is also one of the ratios to measure the profitability of the enterprise.

Ownership. We construct the ratio of direct and indirect of state-owned shares and local government-owned shares to total shares. The indirect shareholders include state-owned enterprises. In China, direct or indirect ownership of commercial banks by either the state or local government often represents excellent service, good credit and low risk. Such banks tend to attract enterprises and individuals for deposit and loan business as well as securities investment.

Moreover, we add macro factors. We use the logarithm of GDP per capita and the logarithm of disposable income per capita at the provincial level where the bank's head office is located as control variables. We also control for time effect and fixed effect to control all time various effects and bank specific effects. Table 2.1 summarizes all the variables and definitions.

[Inserting in Table 2.1]

2.3.4. Summary statistics

Table 2.2 provides summary statistics for our variables. The final sample contains 1183 observations. In terms of risk, commercial banks have a mean *ln(Z-score)*, *NPL rate* and *NPL provision coverage* of 4.41, 1.47 and 0.27 respectively, which are far away of the benchmark of *NPL rate* of (less than) 5% and *NPL provision coverage* of (more than) 150% for commercial banks in China, meaning that the average bank is less likely to be default. In terms of diversity, the geographical diversity (*Branch*) measure indicates that commercial banks have 1091 branches on average, but the number of branches owned by different banks varies very much. The mean of asset diversity (*Div_Asset*) is 0.71, indicating that banks are more diversified on asset. The mean of income diversity (*Div_Income*) is 0.38, indicating that net interest income still accounts for the vast majority of commercial banks' income. Moreover, the average commercial bank has a level of a log of total asset of 26.26, a log of operating income of 22.59. About 25% of the commercial banks are listed and commercial bank has an average level of *ROA* of 0.84. State or state-owned enterprises owned 34.97% shares of commercial banks on average. The average adjusted GDP per capita at provincial level is 0.034 (GDP is over 34 thousand CNY). People live in these provinces where banks headquartered own around 27 thousand CNY disposable income per capita on average (adjusted disposable income per capita is 0.027).

[Inserting in Table 2.2]

2.4. Empirical results

The model we use to assess the relationship between risk and diversity is OLS regressions as follows:

$$Risk_{b,t} = \alpha + \beta DIV_{b,t} + \gamma X_{b,t} + \delta_b + \delta_t + \varepsilon_{b,t} \quad (2.3)$$

where $Risk_{b,t}$ denotes the dependent variable, *lnZ-score, NPL rate* and *NPL provision coverage* of bank *b* in year *t*. $DIV_{b,t}$ denotes our measures of diversity of bank *b* in year *t*, including geographical diversity, product diversity and equity diversity. $X_{b,t}$ denotes control variables of bank *b* in year *t*. δ_b denote bank fixed effects. δ_t denotes time fixed effects. $\varepsilon_{b,t}$ denotes error term of bank *b* in year *t*.

We estimate the impact of corporate diversity on risks, including asset diversity (Div_Asset) and income diversity (Div_Income). The results are reported in Table 2.3. The coefficients of Div_Asset in Models 1, 9 and 10 have a negative significance while the coefficients of Div_Income have a positive significance in Models 3 and 11 and negative significance in Model 7. This indicates that asset diversity could increase bank risk and lower resilience to risk to some extent, and income diversity may lower bank risk. Both results are consistent with our hypotheses. Under the agency risk hypothesis, asset diversity is more reflective of the manager's aggressive business strategy — asset diversity may increase bank risk. In order to meet performance targets and obtain higher rewards, managers with a limited traditional lending business will expand other businesses to increase the volume of other non-loan assets that will involve foreign exchange, derivatives, precious metals, and other relatively high-risk assets. Under the diversification hypothesis, income diversity is much closer to the benefits of diversity — income diversity may lower bank risk. Banks try new businesses to increase their income streams to prevent one of them from being temporarily terminated due to force majeure factors while ensuring the stability of other incomes. For example, the sudden outbreak of COVID-19 in 2020 pressed the pause button on the global economy. As the income of homeowners decreased, they were unable to repay their loans, which led to a corresponding decrease in bank loan income sources. The income from foreign exchange, bonds, stocks, precious metal futures, etc. can compensate for the loss caused by the reduction of loans and ensure the stable operation of the bank.

[Inserting in Table 2.3]

In addition, the control variables also reflect some significance. For example, ROA has a positive effect on bank risk, which indicates that a higher ROA means a bank with higher profits may have lower risks. The GDP of the city where the bank is headquartered and DI also have a positive effect on bank risk, namely increased resilience to risk and reduced bank risk. Cities with a high GDP tend to have more demand for loans and corporate financing, while residents in these cities have relatively high disposable income and therefore low default rates on loans. Many Chinese commercial banks are held by government or state-owned enterprises due to their special characteristics; we therefore consider Ownership, i.e., the percentage of state-owned background holding. However, Ownership is statistically insignificant in all models in Table 2.3. This is because people and investors believe that bank default or bankruptcy is a highly unlikely event nowadays. In China, most ordinary people still perceive the banking industry as a government organization even if the government owns little or no equity and they believe a bank will be supported and saved by a state-owned bank even in the case of bankruptcy.

2.5. Robustness tests

2.5.1. Alternative measures of risk

For robustness tests, we first examine whether our main results are suitable for an alternative measure of bank risk. We replace Stdv.ROA and Volatility as the dependent variable and estimate the regression of Stdv.ROA and Volatility on diversity variables and control variables for all samples. Volatility is measured as the volatility of the rate of return by using the weekly closing price from the Reuters database (Refinitiv). The results are reported in Table 2.4 and 2.5.

[Inserting in Table 2.4]

[Inserting in Table 2.5]

It is clear that no variables are statistically significant in terms of Volatility; this means that Volatility cannot fully represent risk for the banking industry. The reasons are as follows: first, in terms of stock rules, A-shares have a 10% (listed in Main-board Market) or 20% (listed in Second-board Market) daily range of ups and downs, which is less volatile in one day than U.S. stocks without any limit on ups and downs. A-shares cannot be bought and sold on the same day; in other words, shares bought on the same day can only be sold the next day. Unlike the long-short mechanism of European and American stocks, A-shares cannot be shorted. Second, in terms of stock characteristics, whereas U.S. stocks are bought mainly for investment, holders of A-share are more speculative and most of them only care about the difference between the up and down stock price. The U.S. stock market is dominated by institutional investors, while the Chinese stock market is dominated by individuals, most of whom have little knowledge of finance. In terms of fundamentals, the fundamentals of A-share companies do not match the share price; for example, while the performance of U.S. companies is often reflected in the share price, the latter often falls even if the company's performance is very good. A-share companies pay very low dividends, and many individual investors only focus on the share price itself and ignore dividends, which also causes holders of A-shares to speculate rather than invest. Therefore, based on the peculiarities of the Chinese stock market, volatility can hardly reflect banks' ex ante risk or expected risk.

2.5.2. Subsamples

2.5.2.1. Listed and non-listed banks

In this section, we divide the samples into listed and non-listed banks and then estimate the regression of risks on corporate diversity, respectively. The results are presented in Tables 2.6. Corporate diversity is more significant for listed banks than non-listed banks. However, corporate diversity for listed banks is more dominated by the agency risk hypothesis. Both asset diversity and income diversity have a negative effect on bank risk (asset diversity lowers the lnZscore and NPL provision coverage and increases the NPL rate in Models 1, 2, 5, 6 and 9 while income diversity increases the NPL rate in Models 7, 8 and 12); this is inconsistent with the results of income diversity in the baseline model. Managers in listed banks will adopt more aggressive expansion strategies relative to those of non-listed banks because their bonus and personal rewards are much higher than for managers in non-listed banks. As listed banks continue to expand, the banks' revenues and total revenue categories grow with them, accompanied by larger asset volumes and a greater variety of asset classes. Hence, corporate diversity lowers risk in listed banks.

[Inserting in Table 2.6]

2.5.2.2. Exclude “TBTF” banks

We further estimate the regression model excluding “too big to fail” (TBTF) banks whose total assets do not exceed 321 billion CNY (at 90% level of the samples). In some cases, banks with large assets are more likely to pursue business expansion. Therefore, we exclude “too big to fail” banks and the results are reported in Tables 2.7.

[Inserting in Table 2.7]

The results of corporate diversity are consistent with our baseline model. The coefficients of asset diversity in Models 1, 9 and 10 are statistically significant and have a negative impact on bank risk, which is consistent with the dominance of the agency risk hypothesis—managers seek their rewards and expand the business aggressively with higher risk and cost, which may harm shareholders' interest. The results of income diversity in Models 7 and 11 show the predominance of the diversification hypothesis— the bank is diversifying its income by opening up and trying new businesses to increase revenue, which makes it more stable for future operations.

2.5.3. Moderating effect

Some scholars argue that geographical diversity can cover more markets and increase revenue. Goetz, Laeven and Levine (2016) believe that appropriate geographical diversity can reduce risk. However, distance makes it difficult for the bank to manage and control its subsidiaries, which may give rise to poor asset quality (Brickley, Linck, and Smith, 2003; Berger, et al., 2005). Zamore, Beisland and Mersland (2019) argue that geographical diversity comes with more credit risks, and this is magnified among microfinance institutions. Simoens and Vander Vennet (2021) find that in the face of global events such as Covid-19, geographical diversity cannot act as a shock absorber but product diversity and loan diversity can effectively prevent a significant decline in bank stocks. Berger et al. note (2015) that the market risk hypothesis effect outweighs the diversity hypothesis because of foreign market uncertainty and that diversity does not reduce risk. In this section, we will construct a new variable geographical diversity and use it to interact with asset diversity and income diversity to see if it moderates the impact of these variables on risk.

The most common measure of geographical diversity in banking studies is the number of branches (Aguirregabiria, et al., 2016; Zamore, et al., 2019; Cai, et al., 2016). Zamore, et al. (2019), for example, note that a bank with more branches has more credit risks, while Cai et al. (2016) find that geographical expansion with more branches improves the banks' performance. However, Deng and Elyasiani (2008) argue that it is hard to capture the distance between the headquarters and a branch by measuring the number of agencies. In China, commercial banks need to meet certain criteria to set up branches. According to the Commercial Bank Law of the People's Republic of China, commercial banks are required to submit financial information for the previous two years to the banking supervision and administration agency of the State Council; this includes the operating premises of the branch and the amount of working capital allocated to the branch, which must not exceed 60% of the capital of the headquarters. We believe that the Commercial Bank Law sets the threshold for the establishment of branches, giving them a certain regional character, namely, commercial bank branches are established primarily to serve the people of that region. Hence, we use the number of the bank's branches, including branches, subbranches and branch network, as the variable of geographical diversity. In the regression model, we measure geographical diversity as the number of branches over 1,000. We then construct the interaction variable GeoAsset (geographical diversity * asset diversity) and GeoIncome (geographical diversity * income diversity). The results are reported in Table 2.8.

[Inserting in Table 2.8]

It is clear see that the coefficient of the interaction variable between geographical diversity and asset diversity in Model 6 is significantly positive, while that of the interaction variable between geographical diversity and income diversity is insignificant, which indicates that the moderating variable geographical diversity weakly affects the negative relationship between asset diversity and bank risk, in other words, a bank with more branches will inhibit the impact of its asset diversity on reducing bank risk. Banks increase asset diversity through geographic expansion. However, banks are restricted by policies to set up a new branch, which will lead to higher costs if banks expand geographically. Thus, the impact of asset diversity on reducing bank risk is inhibited when bank managers are unable to effectively manage the addition of new branches.

2.5.4. Instrumental variables and endogeneity

This section addresses the potential endogeneity of the corporate diversity variable. There could be a causal link between policy, geographic expansion and corporate diversity. For example, when the government introduces policies to encourage banks to increase the number of branches to facilitate services to the public, the number of bank branches will rise. The more branches a bank has, the more it is likely to increase income and asset. Bank headquarters in or near the economic center are more likely to pursue business expansion than those far from the economic center in other provinces. This may result in a correlation between our diversity variables and the error term. Therefore, we use an instrumental variable (IV) estimation to extract the exogenous component of asset diversity and income diversity in assessing the influence of corporate diversity on risk.

We construct two dimensions: since Beijing, Shanghai and Shenzhen are Top 3 GDP cities, there are three economic centres based on Beijing, Shanghai and Shenzhen, namely, Beijing-Tianjin-Tanggu Economic Centre centred in Beijing, Yangtze River Delta Economic Zone centred in Shanghai, and Pearl River Delta Economic Zone centred in Shenzhen. We measure the distance by using Baidu Map to capture the distance between a bank's headquarter and Beijing, Shanghai and Shenzhen, choosing the minimum value. If a bank headquarters among Beijing, Shanghai and Shenzhen, we set distance as 10 kilometers. Then we construct $ln(Distance)_{b,j}$, the natural logarithm of kilometers between a bank's headquarter and economic centre, to capture the radiation effect of the economic centre. Second, we construct *Policy* as another IV, a dummy variable equals to 1 if there is a policy related to geographic expansion, and 0 otherwise. Taking into account the lag in policy implementation, we also add another instrumental variables that are $Policy_{t-1}$, a dummy variable equals to 1 if there is a policy related to geographic expansion in the previous year, and 0 otherwise. In the first stage, we examine the following equation:

$$Branch_{b,t} = \alpha + \beta_1 ln\,(Distance)_{b,t} + \beta_2 Policy_t + \beta_3 Policy_{t-1} + \varepsilon_{b,t} \qquad (2.4)$$

The results are reported in Table 2.9. The variable $ln(Distance)_{b,t}$, $Policy_t$ and $Policy_{t-1}$ in first stage in Model 1 are positive and significant to asset diversity, while $ln(Distance)_{b,t}$ in first stage in Model 5 is negative and significant to income diversity, and $Policy_{t-1}$ is positive and significant to income diversity. In the second stage, we examine Equation (3) considering the IV variables. The asset diversity shows insignificant. We further use Durbin and Wu-Hausman to test if the instrument variables are exogenous. With a p-value of 0.15, 1.50 and 1.32 respectively, the null hypothesis of $ln(Distance)_{b,t}$, $Policy_t$ and $Policy_{t-1}$ is exogenous and is therefore not rejected. The income diversity proves to be significant in Model 6 compared to baseline models, which supports to our previous results, which is consistent to our diversification hypothesis as income diversity may lower bank risk. We also use Durbin and Wu-Hausman to test if the instrument variables are exogenous. With a p-value of 10.42, the null hypothesis $ln(Distance)_{b,t}$, $Policy_t$ and $Policy_{t-1}$ is exogenous and is therefore rejected at 1%.

[Inserting in Table 2.9]

2.6. Conclusion

How does corporate diversity affect bank risk? To the best of our knowledge, this paper is the first to assess the role of diversity from two perspectives in bank risk in a quantitative method using Chinese bank data. We use different measures of risks, control for moderating effect, potential endogeneity and consider different subsamples. The main findings are as follows: first, for all the Chinese commercial banks, asset diversity is consistent with the predominance of the agency risk hypothesis, whereas income diversity is consistent with the predominance of the diversification hypothesis. Second, listed banks are more sensitive to corporate diversity. Corporate diversity are consistent with the predominance of the agency risk hypothesis — they increase the risk of listed banks because their bank managers adopt more aggressive business strategies and geographic expansion strategies in order to obtain a higher bonus. When there are too many branches, the management and control of the banks becomes difficult, thus increasing bank risk.. Third, the moderating variable geographical diversity weakly affects the negative relationship between asset diversity and bank risk. Fourth, our 2SLS estimates show that income diversity may lower bank risk. The closer the bank is to the economic center, the easier it will be for outward business expansion. Most of China's resources are found in economic centers. Beijing, Shanghai and Shenzhen are ranked Top 3 in China in terms of GDP. Therefore, the closer the bank is to the economic center, the faster it can obtain the benefits from it.

The main contribution of this article is the quantitative analysis of the risks of diversity in the Chinese banking industry, setting the groundwork for further research on bank diversity. To the best of our knowledge, this paper is the first to introduce the moderating variable geographical diversity to discuss whether geographical diversity strengthens or weakens the effect of corporate diverity on bank risk. In fact, a bank with more branches will inhibit the impact of its asset diversity on reducing bank risk. From the perspective of bank management, banks that diversify geographically need to consider whether this will increase their risk exposure; when banks diversify their assets, they need to consider the ratio of investment in risky and risk-free assets. From the perspective of policymakers, policy instruments should be adopted to effectively control systematic risks while encouraging bank expansion. At the same time, as shareholders of banks, government institutions should fully assume their regulatory functions to stop banks from abusing their powers in the name of linking with government institutions and endlessly increasing their risk exposure.

The paper also has some limitations. Some banks have been listed for a very short period of time and data from the listing is therefore insufficient to predict and reflect the subsequent performance; this means data and results must be continuously updated. The data selection only considered joint-stock banks and city commercial banks, while many rural commercial banks were excluded due to incomplete data. A more comprehensive study in the future should include rural commercial banks in the sample as long as there is full disclosure of their financial data.

Table 2.1: Variable Definitions.

This table provides variable names, definitions, and data sources.

Variables	Definition	Source
Dependent variables		
Ln(Z-score)	The logarithm of Z-score. Z-score calculated as (ROA+Equity/Asset)/Stdv.ROA. The larger the Z-score, the less risk a bank has.	Calculate
NPL rate	Non-performing loan rates, a measure of risk defined as the proportion of a loan portfolio that is in arrears for longer than 90 days.	Annual reports
NPL provision coverage	A measure of risk defined as the portion of the non-performing loans covered by provisions. The more NPL provision coverage, the more resilient the bank is to risk. In the regression model, we adopt NPL provision coverage/1,000.	Annual reports
Independent variables		
Div_Asset	A measure of corporate diversity calculated as 1-|(net loans-other earning assets)/total earning assets|.	Calculate; Annual reports
Div_Income	A measure of corporate diversity calculated as 1-|(net interest income-other operating income)/total operating income|.	Calculate; Annual reports
Control variables		
lnSize	The logarithm of asset.	Annual reports
Listed	A dummy that takes a value of 1 if the bank is publicly tradable, and 0 otherwise.	Annual reports
lnIncome	The logarithm of operating income.	Annual reports
ROA	Return on assets.	Calculate; Annual reports
Ownership	It is calculated as the ratio of direct and indirect state-owned shares and local government-owned shares to total shares.	Calculate; Annual reports
GDP	GDP per capita at the provincial level. We employ GDP divided by 1 million CNY in the regression.	National Bureau of Statistics
DI	Disposable income per capita at the provincial level. We employ DI divided by 1 million CNY in the regression.	National Bureau of Statistics
Branch	A measure of geographical diversity defined as the number of branches that a bank has. In the regression model, we adopt Branch/1,000.	Annual reports
Time FE	Time fixed effects.	
Bank FE	Entity fixed effects.	

Table 2.2: Summary statistics.

This table shows summary statistics for the sample.

Variables	N	Mean	Std.dev.	Min.	Max.	Median
Dependent variables						
Ln(Z-score)	1183	4.41	0.98	1.46	9.20	4.33
NPL rate(%)	1183	1.47	0.94	0.00	13.97	1.41
NPL provision coverage	1183	0.27	0.32	0.03	5.97	0.21
Independent variables						
Div_Asset	1183	0.71	0.22	0.04	1.00	0.76
Div_Income	1183	0.38	0.26	0.00	1.00	0.34
Control variables						
lnSize	1183	26.26	1.63	23.11	31.14	25.90
lnIncome	1183	22.59	1.62	19.56	27.51	22.21
Listed	1183	0.25	0.43	0.00	1.00	0.00
ROA(%)	1183	0.84	0.37	-1.76	2.47	0.84
Ownership	1183	0.35	0.23	0.00	1.00	0.32
GDP	1183	0.03	0.02	0.00	0.11	0.03
DI	1183	0.03	0.01	0.01	0.07	0.02
Branch	1183	1091.53	4222.94	6.00	40056.00	115.00

Table 2.3: Corporate diversity and bank risk - OLS regressions.

This table reports OLS regressions of the relation between the corporate diversity and risks over the period 2009–2020. The dependent variables are ln(Z-score), NPL rate and NPL provision coverage. Models 2, 4, 6, 8, 10, 12 include the control variables. All regressions include bank fixed effects and time fixed effects. Robust t-statistics are in parentheses. ∗, ∗∗, ∗∗∗ denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable:	Ln(Z-score)				NPL rate(%)				NPL provision coverage			
Div_Asset	-0.468***	-0.181			0.107	-0.185			-0.144***	-0.121**		
	(-3.27)	(-1.25)			(0.80)	(-1.44)			(-2.98)	(-2.41)		
Div_Income			0.252**	0.116			-0.197*	-0.027			0.074*	0.033
			(2.03)	(0.97)			(1.69)	(-0.26)			(1.75)	(0.77)
lnSize		-0.409*		-0.444*		-0.874***		-0.930***		0.091		0.061
		(-1.73)		(-1.90)		(-4.15)		(-4.47)		(1.09)		(0.74)
lnIncome		0.247		0.266		0.759***		0.792***		-0.063		-0.046
		(1.32)		(1.43)		(4.54)		(4.76)		(-0.95)		(-0.70)
Listed		-0.126		-0.120		-0.080		-0.062		0.056		0.063
		(-1.03)		(-0.99)		(-0.74)		(-0.57)		(1.30)		(1.48)
ROA(%)		0.992***		1.000***		-1.411***		-1.403***		0.030		0.035
		(7.55)		(7.62)		(-12.06)		(-11.99)		(0.64)		(0.76)
Ownership		0.122		0.094		0.156		0.133		0.059		0.042
		(0.45)		(0.34)		(0.64)		(0.55)		(0.61)		(0.43)
GDP		9.769**		9.092*		-21.357***		-21.727***		7.309***		6.956***
		(2.09)		(1.95)		(-5.13)		(-5.22)		(4.45)		(4.22)
DI		-10.475		-9.723		-21.354**		-19.262**		8.895***		9.802***
		(-1.12)		(1.04)		(-2.56)		(-2.32)		(2.70)		(2.98)

(Continue Table 2.3)

Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1183	1183	1183	1183	1183	1183	1183	1183	1183	1183	1183	1183
R-squared	0.19	0.28	0.18	0.28	0.22	0.38	0.22	0.37	0.10	0.13	0.09	0.12

Table 2.4: Diversity and the volatility of ROA - OLS regressions.

This table reports OLS regressions of the relation between the diversity and the volatility of ROA over the period 2009–2020. The dependent variable is the volatility of ROA by using a 3-year rolling window. Models 2 and 4 include control variables. All regressions include bank fixed effects and time fixed effects. Robust t-statistics are in parentheses. ∗, ∗∗, ∗∗∗ denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Div_Asset	0.003	-0.031		
	(0.14)	(-1.48)		
Div_Income			-0.029	-0.019
			(-1.57)	(-1.13)
lnSize		0.000		-0.012
		(0.00)		(-0.34)
lnIncome		-0.033		-0.027
		(-1.25)		(-1.01)
Listed		0.056***		0.060***
		(3.19)		(3.43)
ROA(%)		-0.171***		-0.170***
		(-9.05)		(-8.98)
Ownership		0.046		0.043
		(1.17)		(1.09)
GDP		-1.111*		-1.139*
		(-1.65)		(-1.70)
DI		3.319**		3.801***
		(-2.46)		(2.83)
Bank fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Observations	1183	1183	1183	1183
R-squared	0.07	0.21	0.07	0.21

Table 2.5: Diversity and the volatility of rate of return - OLS regressions.

This table reports OLS regressions of the relation between the diversity and the volatility of rate of return over the period 2009–2020. The dependent variable is the volatility of rate of return. We calculate the volatility by using the 52-week closing price from Reuters (Refinitiv). Then we replace the logarithm of volatility of the rate of return in 52 weeks as the dependent variable. As not all the banks are listed, we only consider the listed banks. Models 2 and 4 includes the control variables. All regressions include bank fixed effects and time fixed effects. Robust t-statistics are in parentheses. $*$, $**$, $***$ denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Div_Asset	0.001	-0.006		
	(0.30)	(-1.00)		
Div_Income			-0.005	-0.000
			(-0.61)	(-0.03)
lnSize		0.013		0.013
		(1.08)		(1.04)
lnIncome		-0.028***		-0.028***
		(-2.81)		(-2.78)
ROA(%)		-0.005		-0.004
		(-0.76)		(-0.60)
Ownership		0.014		0.013
		(1.07)		(0.99)
GDP		0.014		0.067
		(0.07)		(0.33)
DI		-1.154***		-1.022**
		(-2.72)		(-2.52)
Bank fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Observations	277	277	277	277
R-squared	0.46	0.51	0.46	0.51

Table 2.6: Corporate diversity and bank risk for listed and non-listed bank - OLS regressions.

This table reports OLS regressions of the relation between the corporate diversity and risks of listed and non-listed bank over the period 2009–2020. The dependent variables are ln(Z-score), NPL rate and NPL provision coverage. Model 2, 4, 6, 8, 10, and 12 include the control variables. All regressions include bank fixed effects and time fixed effects. Robust t-statistics are in parentheses. ∗, ∗∗, ∗∗∗ denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable:			Ln(Z-score)				NPL rate(%)				NPL provision coverage	
Panel A: Listed												
Div_Asset	-0.956***	-0.668***			0.752***	0.228*			-0.043*	0.010		
	(-4.22)	(-2.84)			(4.60)	(1.79)			(-1.84)	(0.44)		
Div_Income			0.150	-0.045			0.856***	0.774***			-0.029	-0.087**
			(0.36)	(-0.11)			(2.90)	(3.58)			(-0.68)	(-2.27)
lnSize		1.250**		1.203**		-2.162***		-2.188***		0.188***		0.194***
		(2.29)		(2.17)		(-7.31)		(-7.54)		(3.62)		(3.76)
lnIncome		-0.677		-0.673		2.178***		2.047***		-0.102**		-0.087*
		(-1.50)		(-1.45)		(8.86)		(8.40)		(-2.37)		(-2.02)
ROA(%)		1.654***		1.765***		-2.108***		-2.177***		0.127***		0.129***
		(5.90)		(6.24)		(-13.84)		(-14.70)		(4.73)		(4.89)
Ownership		-0.327		-0.476		0.482		0.491		0.021		0.028
		(-0.58)		(-0.83)		(1.57)		(1.63)		(0.39)		(0.53)
GDP		-4.323		1.459		-14.227***		-15.016***		5.009***		4.785***
		(-0.48)		(0.16)		(-2.91)		(-3.20)		(5.81)		(5.75)
DI		-4.035		10.384		-13.308		-14.889		4.595**		3.993**
		(-0.23)		(0.60)		(-1.39)		(-1.65)		(2.72)		(2.48)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(Continue Table 2.6)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable:	Ln(Z-score)				NPL rate(%)				NPL provision coverage			
Observations	297	297	297	297	297	297	297	297	297	297	297	297
R-squared	0.50	0.57	0.48	0.56	0.35	0.68	0.32	0.70	0.27	0.48	0.27	0.49
Panel B: Non-listed												
Div_Asset	-0.200	0.078			-0.282	-0.360**			-0.133*	-0.168**		
	(-1.03)	(0.42)			(-1.47)	(-2.00)			(-1.85)	(-2.29)		
Div_Income			0.196	0.143			-0.204	-0.113			0.045	0.029
			(1.40)	(1.07)			(-1.47)	(-0.88)			(0.86)	(0.54)
lnSize		-0.633**		-0.591**		-0.746***		-0.848***		0.107		0.074
		(-2.31)		(-2.17)		(-2.83)		(-3.25)		(1.00)		(0.69)
lnIncome		0.550**		0.531**		0.516**		0.569***		-0.069		-0.049
		(2.53)		(2.46)		(2.48)		(2.75)		(-0.81)		(-0.57)
ROA(%)		0.894***		0.890***		-1.277***		-1.263***		0.007		0.013
		(5.90)		(5.89)		(-8.80)		(-8.70)		(0.12)		(0.21)
Ownership		0.346		0.352		0.048		0.020		0.042		0.028
		(1.10)		(1.11)		(0.16)		(0.07)		(0.34)		(0.22)
GDP		10.492		10.709		-27.301***		-28.129***		9.129***		8.768***
		(1.45)		(1.49)		(-3.95)		(-4.07)		(3.23)		(3.10)
DI		-52.921***		-54.798***		-8.504		-8.358		5.106		3.904
		(-2.62)		(-2.71)		(-0.44)		(-0.43)		(0.65)		(0.49)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	886	886	886	886	886	886	886	886	886	886	886	886
R-squared	0.11	0.22	0.11	0.22	0.21	0.34	0.21	0.34	0.10	0.12	0.10	0.12

Table 2.7: Corporate diversity and bank risk for non- “too big to fail” bank - OLS regressions.

This table reports OLS regressions of the relation between the corporate diversity and risks excluding “too big to fail” banks over the period 2009–2020. The assets of non-TBTF bank are not more than 321 billion CNY (at the 90% level of total samples). The dependent variables are ln(Z-score), NPL rate and NPL provision coverage. Models 2, 4, 6, 8, 10, and 12 include the control variables. All regressions include bank fixed effects and time fixed effects. Robust t-statistics are in parentheses. ∗, ∗∗, ∗∗∗ denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable:	Ln(Z-score)				NPL rate(%)				NPL provision coverage			
Div_Asset	-0.318*	-0.060			-0.072	-0.278*			-0.129**	-0.130**		
	(-1.96)	(-0.37)			(-0.46)	(-1.89)			(-2.26)	(-2.23)		
Div_Income			0.203	0.104			-0.226*	-0.083			0.074*	0.041
			(1.57)	(0.83)			(1.82)	(-0.72)			(1.65)	(0.89)
lnSize		-0.450*		-0.445*		-0.852***		-0.923***		0.087		0.066
		(-1.81)		(-1.80)		(-3.75)		(-4.09)		(0.96)		(0.74)
lnIncome		0.311		0.310		0.703***		0.748***		-0.054		-0.039
		(1.59)		(1.60)		(3.94)		(4.21)		(-0.76)		(-0.55)
Listed		-0.106		-0.108		-0.101		-0.064		0.054		0.064
		(-0.83)		(-0.85)		(-0.87)		(-0.55)		(1.16)		(1.39)
ROA(%)		0.987***		0.990***		-1.416***		-1.403***		0.024		0.031
		(7.28)		(7.31)		(-11.42)		(-11.31)		(0.50)		(0.62)
Ownership		0.202		0.197		0.034		0.019		0.068		0.059
		(0.70)		(0.68)		(0.13)		(0.07)		(0.64)		(0.56)
GDP		13.257**		13.097**		-25.550***		-25.952***		7.529***		7.292***
		(2.42)		(2.40)		(-5.10)		(-5.18)		(3.77)		(3.65)
DI		-24.300*		-25.847*		-11.214		-9.964		8.946*		8.343*
		(-1.82)		(-1.91)		(-0.92)		(-0.81)		(1.83)		(1.69)

(Continue Table 2.7)

Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1064	1064	1064	1064	1064	1064	1064	1064	1064	1064	1064	1064
R-squared	0.14	0.24	0.14	0.24	0.21	0.37	0.22	0.37	0.10	0.13	0.09	0.12

Table 2.8: Moderating effect of total samples.

This table reports the results of moderating effect of geographical diversity. We measure Branch as geographical diversity. The interaction variable GeoAsset denotes geographical diversity * asset diversity, GeoIncome denotes geographical diversity * income diversity. The dependent variables are ln(Z-score), NPL rate and NPL provision coverage. Model 2, 4, 6, 8, 10, and 12 include the control variables. All regressions include bank fixed effects and time fixed effects. Robust t-statistics are in parentheses. *, **, *** denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		Ln(Z-score)			NPL rate(%)				NPL provision			
Div_Asset	-0.490***	-0.155			0.019	-0.264**			-0.135***	-0.116**		
	(-3.28)	(-1.05)			(0.13)	(-1.98)			(-2.68)	(-2.21)		
Div_Income			0.226*	0.091			-0.185	-0.088			0.070	0.062
			(1.79)	(0.76)			(-1.57)	(-0.80)			(1.64)	(1.45)
Branch	-0.004	-0.015	-0.026	-0.010	-0.025	-0.024	0.021	0.002	0.001	0.001	-0.007	-0.002
	(-0.11)	(-0.51)	(-0.74)	(-0.30)	(-0.85)	(-0.88)	(0.62)	(0.08)	(0.13)	(0.07)	(-0.55)	(-0.15)
GeoAsset	0.010	0.019			0.043**	0.036**			-0.004	-0.003		
	(0.50)	(0.97)			(2.20)	(2.00)			(-0.59)	(-0.44)		
GeoIncome			0.106	0.033			-0.048	0.006			0.016	-0.001
			(1.26)	(0.41)			(-0.61)	(0.08)			(0.56)	(-0.03)
lnSize		-0.417*		-0.417*		-0.728***		-0.790***		0.057		0.027
		(-1.80)		(-1.81)		(-3.46)		(-3.78)		(0.68)		(0.33)
lnIncome		0.225		0.239		0.669***		0.718***		-0.009		0.002
		(1.21)		(1.29)		(3.97)		(4.27)		(-0.14)		(0.03)
Listed		-0.149		-0.136		-0.022		0.018		0.034		0.039
		(-1.22)		(-1.12)		(-0.20)		(0.17)		(0.79)		(0.90)

(Continue Table 2.8)

ROA(%)		1.025***		1.024***		-1.539***		-1.531***		0.053		0.059
		(7.93)		(7.94)		(-13.15)		(-13.07)		(1.14)		(1.28)
Ownership		0.201		0.202		-0.024		-0.010		0.097		0.076
		(0.73)		(0.74)		(-0.09)		(-0.04)		(0.99)		(0.77)
ROA(%)		1.025***		1.024***		-1.539***		-1.531***		0.053		0.059
		(7.93)		(7.94)		(-13.15)		(-13.07)		(1.14)		(1.28)
Ownership		0.201		0.202		-0.024		-0.010		0.097		0.076
		(0.73)		(0.74)		(-0.09)		(-0.04)		(0.99)		(0.77)
GDP		1.036*		0.995*		-1.152**		-1.138**		0.568***		0.600***
		(1.77)		(1.69)		(-2.17)		(-2.13)		(2.72)		(2.85)
DI		1.657		1.752		-0.458		-0.383		-1.794***		-1.847***
		(1.26)		(1.33)		(-0.39)		(-0.32)		(-3.83)		(-3.92)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1183	1183	1183	1183	1183	1183	1183	1183	1183	1183	1183	1183
R-squared	0.1866	0.2817	0.1825	0.2811	0.2260	0.3608	0.2244	0.3573	0.0982	0.1158	0.0932	0.1115

Table 2.9: Endogeneity of total samples.

This table reports the results of the instrumental variable (IV) estimation that controls for the endogeneity of corporate diversity. The instrument is $ln(Distance)_{b,j}$, the natural logarithm of kilometers between bank headquarters and the economic center; $Policy_t$ and $Policy_{t-1}$, dummy variables that are equal to 1 if there is a policy related to geographic expansion in the same year and in the previous year, respectively. The first line is the dependent variable. Model 1 is the first-stage regression of the IV estimation. Models 2, 3, 4 and 5 are the second-stage regressions of the IV estimation with different dependent variables. F-statistic indicates whether the IV estimation is significant in the first-stage regression. All regressions include bank fixed effects and time fixed effects. Robust t-statistics are in parentheses. $*$, $**$, $***$ denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Asset diversity	Ln(Z-score)	NPL rate(%)	NPL provision	Income diversity	Ln(Z-score)	NPL rate(%)	NPL provision
	First stage	Second stage	Second stage	Second stage	First stage	Second stage	Second stage	Second stage
Div_Asset		0.023	-0.086	0.154				
		(0.03)	(-1.25)	(0.59)				
Div_Income						3.383**	2.833**	-0.517
						(2.42)	(2.37)	(-1.35)
Ln(Distance)	0.031***				-0.021***			
	(7.77)				(-4.39)			
Policy	0.040***				-0.005			
	(3.14)				(-0.30)			
$Policy_{t-1}$	0.022*				0.033**			
	(1.76)				(2.20)			
lnSize		0.120	-0.561***	0.138*		0.291	-0.606***	0.145***
		(0.56)	(-2.88)	(1.87)		(1.45)	(-3.54)	(2.65)
lnIncome		0.029	0.517***	-0.150**		-0.157	0.545***	-0.154***
		(0.14)	(2.70)	(-2.08)		(-0.78)	(3.15)	(-2.79)

(Continue Table 2.9)

Listed		-0.130	-0.044	0.007		-0.209	-0.057	0.010
		(-1.27)	(-0.46)	(0.21)		(-1.61)	(-0.51)	(0.28)
ROA(%)		0.295***	-1.569***	0.255***		0.307**	-1.558***	0.253***
		(2.96)	(-17.14)	(7.36)		(2.26)	(-13.39)	(6.79)
Ownership		0.093	-0.105	0.102**		0.142	-0.053	0.092*
		(0.73)	(0.91)	(2.33)		(0.82)	(-0.36)	(1.95)
GDP		0.085**	-0.071*	-0.007		0.106*	-0.064	-0.009
		(2.02)	(-1.86)	(-0.49)		(1.87)	(-1.33)	(-0.55)
DI		0.506***	0.071	-0.045		0.074	-0.179	0.001
		(3.86)	(0.59)	(-1.00)		(0.34)	(-0.97)	(0.01)
Observations	1183	1183	1183	1183	1183	1183	1183	1185
F-statistic	24.55				7.94			
Endogenous test:		0.15	1.50	1.32		10.42	8.37	2.31
p-value		(not reject)	(not reject)	(not reject)		(reject at 1%)	(reject at 1%)	(not reject)

Table 2.10: Policy related to diversity.

This table reports the policies related to diversity since 2009

Time	Policy	Related article
1995.07 first implemented 2003 first amendment 2015 second amendment 2020 third amendment	Law of the People's Republic of China on Commercial Banks	Article 11,13,19,21,22
2018.12	Guiding Opinions of the China Banking and Insurance Regulatory Commission on Regulating Out-of-Area Non-Licensed Institutions of Banking Financial Institutions	Article 6
2018.12	Measures for the Administration of Wealth Management Subsidiary Companies of Commercial Banks	
2015.03	Notice of the General Office of the China Banking Regulatory Commission on Effectively Providing Rural Financial Services in 2015	Article 3
2015.03	Guiding Opinions of the China Banking Regulatory Commission on Deepening the Financial Services for Small- and Micro-sized Enterprises	Article 3
2014.12	Guiding Opinions of the China Banking Regulatory Commission on Further Promoting the Sound Development of Village Banks	Article 1
2014.03	Notice of the General Office of the China Banking Regulatory Commission on Banks' Effective Provision of Financial Services for Rural Areas in 2014	Article 2,3
2012.06	Guiding Opinions of the General Office of China Banking Regulatory Commission on the implementation of financial services in villages and communities by rural small and medium-sized financial institutions	Article 3
2011.03	Notice of the General Office of China Banking Regulatory Commission on Further Promoting Basic Financial Services in Blank Townships	

Source: China Banking and Insurance Regulatory Commission

CHAPTER 3

Board Diversity and Bank Risk

Abstract: This paper contributes to the evaluation of the impact of board diversity on bank risk in the Chinese banking industry. We created a new variable by standardizing the percentage of females on the board, age difference, educational background, and financial expertise. We use the Zscore logarithm and stock volatility as measures of bank risk. The samples cover all the listed Chinese commercial banks in the Shanghai Stock Exchange, Shenzhen Stock Exchange and Hong Kong Stock Exchange over the period from 2006 to 2021. Our main finding is that bank risk can be lower if there is a more diversified board (in particular in small banks) or a more diversified supervisory board (in particular in large banks); this is consistent with agency hypothesis whereby boards with more diversity can better maintain board independence to avoid agency problems between management and shareholders as well as aggressive strategies in pursuit of management's interests at the expense of those of shareholders. In a univariate analysis, we find that while diversity of age, educational background and financial expertise can reduce bank risk to varying degrees, female presence on the board does not have a significant impact on bank risk. In quantile regression analysis, we find demographic factors (female and age) have an inverted U-shaped relation, while cognitive factors (education background and financial expertise) have a U-shaped relation. Furthermore, we also quantify the government effect, namely the percentage of board members assigned by the government or whose previous job was in a government department but find it has little impact on bank risk. Finally, we use the fraction of board members who are sitting in other firms as instrumental variable, the results are consistent with our findings.

JEL Classification: G21; G28; G30; L25

Keywords: Risk; Board diversity; Bank

3.1. Introduction

Since the financial crisis, previously neglected issues such as corporate governance and reassessment have begun to be taken seriously. Among these issues, board diversity has become particularly salient. In recent years, the diversity of board membership has increasingly been included in the internal policies of Chinese companies as it is considered important to maintaining a good level of corporate governance in the bank, achieving sustainable growth and meeting strategic objectives. In setting the composition of the board of directors, board diversity includes gender, age, cultural and educational background, region, professional experience, skills, knowledge and tenure of service in addition to other regulatory requirements for directors.

While most previous studies focus on a univariate factor of firms’ profitability, performance or risk, such as gender, age, race, education and expertise, some researchers construct a board diversity index but measured in different ways. For example, Harjoto, Laksmana and Yang (2018) measure board diversity using a relation-oriented dimension (gender, race, and age) and task-oriented dimension (tenure and expertise). Ozdemir constructs the board diversity index based on gender, race, age, experience, tenure, and expertise. Jebran, Chen and Zhang (2020) consider board diversity using four dimensions, namely gender, age, tenure and education. Bernile, Bhagwat and Yonker (2018) construct a multidimensional board index including gender, age, race, education, expertise and the mean number of other boards in the Standard and Poor’s (S&P) 1500 on which current members serve.

To the best of our knowledge, studies focus predominantly on the banking industry in U.S. or Europe but few publications address the situation in China. China's banking industry is different from that of the United States. In the United States, the Federal Reserve is at the core, commercial banks are the main body and there is a financial market-oriented banking system. In contrast, the central bank is at the core of China's banking industry and the four major banks are the main body, but there are also urban commercial and agricultural commercial banks across small cities and urban developments. In terms of responding to external shocks and maintaining financial stability, China's banking sector has been a "buffer" for financial risks to absorb the systemic risks. U.S. bank regulation has gone through a process of deregulation from strong regulation after the 2008 financial crisis to the Volcker Rule changes.

In contrast, China's banking regulation emphasizes strengthening bank risk control and reducing non-performing assets.

This study therefore examines the impact of board diversity (board and supervisory board) on bank risk in China. Following Bernile, Bhagwat and Yonker (2018), we construct a new board diversity index. However, unlike these authors, we only consider the bank industry without addressing director ethnicity or the mean number of other boards because 99% of board members in Chinese banks are Chinese. We also optimize the remaining factors in our case. First, instead of using the Herfindahl concentration indexes for director education from the same university or institution, we calculate these indexes in terms of different educational levels, namely undergraduate, bachelor, master and PhD. Second, rather than using the binary variable for financial expertise provided by RiskMetrics, we calculate the Herfindahl concentration indexes for financial expertise following Minton, Taillard and Williamson (2014). Hence, board diversity in this paper addresses four factors: the fraction of female board members, the standard deviation of board members' age, Herfindahl concentration indexes of board members' education, and Herfindahl concentration indexes of financial experts on the board.

We use data on all listed Chinese commercial banks in the Shanghai Stock Exchange, Shenzhen Stock Exchange and Hong Kong Stock Exchange from 2006 to 2021. There are 56 commercial banks with a total of 408 observations. The banks' financial data comes from the annual report of each bank and weekly stock returns come from Refinitiv Eikon. We also add 48 financial institutions with investment banking and brokerage services with 199 observations in a robustness test. The financial data of financial institutions comes from Eastmoney, a Chinese financial website with financial data and stock information disclosed by listed companies. The weekly stock returns of financial institutions also come from Refinitiv Eikon.

In this paper, we measure lnZ-score and Volatility as bank risk. Z-score is defined as the sum of a bank's mean ROA and mean Capitalization Ratio (equity capital/ total asset) divided by Stdv.ROA (standard deviation of ROA). Volatility is defined as the standard deviation of weekly stock returns. We next construct board diversity by normalizing the factors of the fraction of females, the standard deviation of the age of board members, the HHI index of education background and HHI index of financial expertise as our main variable. We then regress an OLS to evaluate the effect of board diversity and supervisory board diversity on bank risk. Our findings show that board diversity and supervisory board diversity have a negative association with bank risk. Namely, a more diversified board or supervisory board can lower bank risk. We also compare this effect in large and small banks. We find that the effect of board diversity is more marked in small banks, while the effect of supervisory board diversity is more marked in large banks. In the robustness test, we first estimate the impact of univariate factor on bank risk. We find that whereas the fraction of females has no significance for bank risk, the diversity of age, educational background and financial expertise are significant to reduce bank risk to varying degrees. We next quantified the government effect by using the percentage of the board members assigned by the government or whose previous job was in a government department. The results show that the government effect is not significant for bank risk. This is because board members from government agencies only have a supervisory role in board and bank operations and therefore have little influence in bank decision making. We also estimate quantile regressions, and find demographic factors (female and age) have an inverted U-shaped relation, while cognitive factors (education background and financial expertise) have a U-shaped relation. Moreover, we add financial institutions with investment banking and brokerage services to our existing samples. We find that board diversity remains significant, which strengthens our findings i.e., board diversity is a good way to reduce the risk of financial institutions, but it has no significance for Volatility. This is because people in China usually use investment banking and the brokerage industry as a weathervane for the stock market. The movement of investment banking and brokerage services' stocks often gives advance warning of bear and bull markets, making them more vulnerable to risk and emotional trading controls. Furthermore, our additional data includes the last five years encompassing, many international events such as the US-China trade war and the Covid-19 virus, which had a marked impact on the Chinese stock market. Adding the samples of the investment banking and brokerage services amplifies the effect of international events on the financial institutions. In comparison, the impact of board diversification on Volatility seems insignificant. Finally, following by Adam and Ferreira (2009), we adopt the fraction of board members with board connections in other firms as an instrumental variable. The results show that this instrumental variable is valid and it is consistent with our findings.

The rest of the paper is organized as follows. Section 2 presents the data and variables. Section 3 reports the method, results and discussions. Section 4 reports the robustness tests. Section 5 concludes

3.2. Theories and hypothesis development

Board diversity is defined as a diverse combination of characteristics, attributes and expertise brought by board members to the board's processes and decision making (Van der Walt, Ingley, 2003). Current academic theories on board diversity are mainly based on agency theory. The purpose of the board is to create more value through the smooth running of the business. In the framework of agency theory, the board of directors should add value by creating incentives, as well as appointing and replacing management to avoid agency problems (Carter et al., 2003). The board typically consists of inside and outside board members; outside board members should not collude with inside board members to maintain independence and defend shareholders' interests. Board diversity helps address this issue as board members from different backgrounds have an understanding of distinct dimensions of the market and can promote creativity and innovation, as well as reduce agency costs (Carter et al., 2003; Hillman and Dalziel, 2003).

Board diversity can be assessed in demographic and cognitive terms (Hafsi and Turgut, 2013; Ozdemir, 2022). The characteristics of demographic diversity include gender, age and race (Hafsi and Turgut, 2013; Ozdemir, 2022; Hillman and Cannella, 2007; Jebran et al., 2020), while cognitive diversity includes education, expertise, tenure and personality (Ozdemir, 2022; Hafsi and Turgut, 2013; Milliken and Martins, 1996). For example, Jebran et al. (2020) categorize board diversity into relationship-oriented (gender and age) and task-oriented (tenure and education) diversity, observing that higher diversity corresponds to reduced risk of stock crashes based on data from Chinese listed companies from 2003 to 2015. Similarly, Bernile, Bhagwat, and Yonker (2018) construct a multidimensional board diversity index by using the data of all nonfinancial and non-utility firms from the databank ExecuComp and RiskMetrics in the period from 1996 to 2014, and find greater board diversity leads to lower volatility and better performance. Ozdemir (2022) employs a panel dataset of U.S. tourism firms over the period from 2007 to 2016 and establishes a positive link between board diversity and financial performance. Likewise, Hafsi and Turgut (2013) establish a significant relationship between board diversity and social performance using cross-sectional data in the year 2005 from S&P 500 companies.

Previous evidence supports the influence of female directors on corporate risk (Poletti-Hughes and Briano-Turrent, 2019; Zalata, Ntim, Aboud, and Gyapong, 2019). A female presence is critical to improving a company's financial success and reputation (Bear et al., 2010). Gender diverse boards can improve information disclosure and transparency (Gul et al., 2011) as well as the quality of board discussion; it also guarantees that more information is circulated from the board to investors, and increases supervision and monitoring activities

(Abou-El-Sood, 2021; Hillman et al., 2007). Adams and Ferreira (2009) state that women have several favorable characteristics for value assessment, risk-taking, and decision-making. Empirical evidence by Poletti-Hughes and Briano-Turrent (2019), who build a unique dataset covering the period 2004–2014 of four Latin American countries, reveals that adding independent female directors increases venturing risk but not performance hazard risk, while Zalata et al. (2019) indicate female CEOs are more risk aversion by using the sample of US firms over the 1992 to 2014. Gul et al., (2011) investigate the effect of gender-diverse boards in U.S. listed companies on transparency and stock prices, and find gender-diverse board improves stock price informativeness. In a sample of US firms from 1996 to 2003, the results of Adams and Ferreira (2009) show that female directors have a significant impact on board inputs and firm outcomes. Furthermore, by analyzing the dataset of 195 U.S. commercial banks during 2002–2018, Abou-El-Sood (2021) finds that banks with female directors lean towards riskier investments, while Liu et al. (2022), who analyze 11 Australian banks from 2004 to 2019, highlight better risk control in gender-diverse boards. However, Khan et al. (2020) report limited influence of gender diversity on bank risk in Islamic banks.

Board age diversity, often associated with professionalism and extensive work experience, affects risk and performance (Arioglu, 2021). Arioglu's (2021) analysis of Borsa Istanbul listed companies from 2009 to 2017 highlights a positive relationship between board age diversity, company performance, and risk. However, diverse age groups can lead to communication barriers and conflicts in board meetings and discussions, which in turn potentially increase bank risk (Talavera et al., 2018). The study on Chinese banks from 2009 to 2013 by Talavera et al. (2018) uncovers a negative correlation between age diversity and bank profitability, suggesting potential conflicts within heterogeneous boards.

The education and financial expertise of directors also impact risk and performance (Papadimitri et al., 2020; Cheng et al., 2010; Minton et al., 2014). Evidence from Papadimitri et al. (2020), who use a dataset of 1618 firms from 39 countries in fiscal year 2016 and 2017, show that highly qualified directors possess superior risk management capabilities and performance enhancement skills (Papadimitri et al., 2020). Similarly, Cheng et al. (2010) collect 5339 observations over the period 1995 to 2005 and find education level of chairpersons exert significant influences on corporate performance. However, this expertise might lead to more aggressive strategies (Bertrand & Schoar, 2003). Minton et al. (2014) show that financial expertise among independent directors of U.S. banks positively influences bank risk during 2000 to 2008.

Based on agency theory and the literature review, our hypothesis is that a board diversity can better maintain its independence to avoid agency problems between management and shareholders, thus reducing bank risk.

3.3. Data and variables

3.3.1. Sample banks

Our sample comprises all listed Chinese banks for the year from 2006 to 2021. There are 56 Chinese banks listed in Shanghai Stock Exchange, Shenzhen Stock Exchange and Hong Kong Stock Exchange. Our dataset covers 408 observations, including state-owned commercial banks, joint equity commercial banks, city commercial banks and rural commercial banks. Our dataset is an unbalanced panel sample and we acquire bank data from annual reports, including information on board size, board members' age, gender, educational background, financial expertise and financial experience. In addition, we also summarize the financial information from annual reports, including asset size, total equity, total debt, net income. Commercial bank stock volatility come from database Refinitiv Eikon. We exclude the information of the first year of each bank, because in the first year listed banks are usually listed in the middle or end of the year and are accompanied by significant sentiment trading, which does not reflect bank risk very well. Hence, we only have 330 observations when doing regressions on stock volatility.

3.3.2. Variables

3.3.2.1. Measures of risk

We construct two variables to estimate risks. We first measure *Z-score*, with larger values indicating lower overall bank risk as risks (Beltratti and Stulz, 2012; Berger, et al., 2015; Boyd and Runkle, 1993; Houston, et al., 2010; Laeven and Levine, 2009; Meslier, et al., 2016). *Z-score* is calculated as the sum of a bank's mean *ROA* and mean *Capitalization Ratio* (equity capital/ total asset) divided by *Stdv. ROA*. Followed by the methodology of Meslier, et al. (2016), we use the rolling window of 3 years as the *Stdv. ROA* (the volatility of ROA), including the current year and two previous years. We then extract weekly stock price of each bank from the database Refinitiv Eikon since 2008, because the data before 2008 is not available. We then calculate the standard deviation of rate of return as the risk.

3.3.2.2. Measures of board diversity

We construct board diversity index under the instruction of Bernile, Bhagwat and Yonker (2018). In their research, they construct their board diversity by using demographic (observable) and cognitive (unobservable) characteristics. The demographic characteristics include gender, age and ethnicity, while the cognitive characteristics include education background, financial expertise and other board experience. However, different from the case of Bernile, Bhagwat and Yonker (2018), whose sample comprises all nonfinancial and non-utility firms, we focus on a specific industry in China, namely banking sector. 99% of the board members in Chinese banks are Chinese people. It makes no sense to add ethnicity and other board experience. Therefore, our board diversity comprises of only four characteristics, age and gender as a proxy for demographics, education background and financial expertise as a proxy for cognitive characteristics.

The board diversity is calculated as follows. We calculate the fraction of female board members (*Pct_Female*) and the standard deviation of board members' age (*Std_Age*), Herfindahl concentration indexes for education (*HHI_Education*) and financial expertise (*HHI_Expertise*) each year. Specifically, we sort education background into four categories: under bachelor, bachelor, master, PhD or above. For example, if there are 2 members under bachelor, 3 members hold a bachelor, 3 members hold a master and 2 members hold a PhD or above. *HHI_Education* is calculated as $(2/10)^2+(3/10)^2+(3/10)^2+(2/10)^2=0.26$. Similarly, we sort financial expertise into five categories followed by Minton, Taillard and Williamson (2014): (1) has held a board member position at banking institution or the former job was at banking institution, (2) has held a board member position at non-banking financial institution or the former job was at non-banking institution, (3) the former job related to finance but at non-financial institution (e.g. CFO, accountant treasurer), (4) holds an academic position in a related field (e.g. assistant Professor, Professor of finance, economics and accounting), (5) no finance related experience. For example, if there are 2 members in each categories, then *HHI_Expertise* is calculated as $(2/10)^2+(2/10)^2+(2/10)^2+(2/10)^2+(2/10)^2=0.2$.

To create the board diversity index, we next normalize each diversity component by its mean and standard deviation to make its scale equivalent, and then equally weight each factor:

$$\text{BoardDiversity} = \text{Norm}\left(Pct_{Female}\right) + \text{Norm}\left(Std_{Age}\right) - \text{Norm}\left(HHI_{Education}\right) - \text{Norm}\left(HHI_{Expertise}\right) \quad (3.1)$$

Herfindahl concentration indexes (HHI) mean concentration level, higher value indicate higher concentration of the corresponding factor. We therefore indicate diversity by subtract the HHI indexes.

3.3.2.3. Control variables

We employ several control variables for bank characteristics that have been found to affect bank risk. We first control for *Asset.* Larger banks are more diversified and have a greater capacity to absorb risk than smaller banks (Gulamhussen et al., 2014; Berger, Bouwman, Kick, and Schaeck, 2014). Bernile, Bhagwat and Yonker (2018) find asset size has a negative link between the annualized standard deviation of firm's stock returns. We measure as the log of total assets (Berger, et al. 2015; Goetz, Laeven, Levine, 2016; Deng and Elyasiani, 2008; Bernile, Bhagwat and Yonker, 2018).

Our second control is *Board Size*. Previous empirical evidence show that firms with larger board size have less variable on performance, and board size has negative relation with the volatility of monthly stock returns (Cheng, 2008). This is consistent with the results of Bernile, Bhagwat and Yonker (2018), board size is negatively associated with the standard deviation of firm's daily stock returns. Hence, we adopt as the log of the board size.

Our third control is *Board Age*. In our board diversity, we consider age diversity. However, board average age is also one important variable that could affect bank risk. Talavera, Yin and Zhang (2018) investigate argue that board age reflects the diversity of personal values at different stages of life. Do younger board members lack sufficient banking experience? Do older board members be old-fashioned and conservative? We control this variable as the log of board average age.

Our fourth control is *Firm Age*. The longer the bank is established, the more mature the management and operation system the bank has, which can effectively control the risk. Hence, we consider firm age measuring as the log of firm age in our analysis.

ROA (return on assets) is an indicator reflecting the comprehensive utilization effect of the enterprise's assets. The higher the *ROA*, the higher the efficiency of the utilization of assets, which means the bank has good profitability and higher level of management. In other words, the bank has lower risk. As many studies, we add ROA as a control variable (Cheng, 2008; Bernile, Bhagwat and Yonker, 2018; Chen et al., 2020; Sandvik, 2020).

We last control for *Leverage Ratio*. Banks have regulatory oversight on the level of leverage they are can hold. We employ total debt divided by total equity. A high leverage ratio implies higher interest expense, profitability may be erratic, which increase the prospects of risk in return. Moreover, we also control for time effect and fixed effect to control all time various effects and bank specific effects. Table 3.1 summarizes all the variables and definitions.

[Inserting in Table 3.1]

3.3.3. Summary statistics

Table 3.2 provides summary statistics for our variables. Panel A shows the mean, standard deviation, minimum, maximum and medium of all the variables. The final sample contains 408 observations and the volatility of stock returns contains 330 observations. In terms of risk, Chinese banks have a mean *Z-score*, *lnZ-score* of 1.98 (over 1.81), 0.22, and *Volatility* of 0.02, which means the average listing bank is less likely to face a dilemma. The *Board Diversity* in different banks varies from -8.64 (less diversity) to 6.17 (more diversity), but the mean is close to 0. There are 14% female in board. The *HHI_Education* is diversified with 0.39, indicating that the educational background of the board members in the Chinese banking industry is relatively evenly spread between the bachelor, master and doctoral levels. *HHI_Expertise* is 0.33 on average, implying that board members have more or less financial expertise in their former working experience, such as banks, financial institution, non-financial institution but in finance department, professors in financial or economic subjects. Moreover, the average bank has a level of *Asset* of 4.33 trillion CNY, *lnAsset* of 28.04. The maximum *Board Size* in these samples is more than twice the minimum value. The average board member's age is around 54 years old, implying that most board members have already worked for over 20 years. The average leverage ratio is 13.68.

Panel B reports the simple correlations between each components of the *Board Diversity*. The components are all normalized by its mean and standard deviation. Only is the relationship between *Std_Age* and *HHI_Education* negative, other correlations are positive.

[Inserting in Table 3.2]

3.4. Empirical results

In this section, we empirically analyze the effect of board diversity on bank risk. The model we use is OLS regressions as follows:

$$Risk_{b,t} = \alpha + \beta BoardDiversity_{b,t} + \gamma X_{b,t} + \delta_b + \delta_t + \varepsilon_{b,t} \quad (3.2)$$

where $Risk_{b,t}$ denotes the dependent variable, *lnZ-score,* and *Volatility* of weekly stock returns of bank b in year t. $BoardDiversity_{b,t}$ denotes our measures of board diversity that comprises the normalization of the fraction of female, the standard deviation of age, educational background and financial expertise of bank b in year t. $X_{b,t}$ denotes control variables of bank *b* in year *t*. δ_b denotes bank fixed effects. δ_t denotes time fixed effects. $\varepsilon_{b,t}$ denotes error term of bank *b* in year *t*.

The results are presented in Table 3.3. Model 1 shows the regression results of *lnZ-score* on *Board diversity*, including time fixed effect and entity fixed effect. The coefficient of *Board diversity* is 0.0452, positively and statistically significant at the 10% level; this means that when a bank diversifies its board characteristics by 0.01, *Z-score* increases by about 0.0452%. Model 2 includes all control variables. The coefficient of *Board diversity* is still positive but becomes statistically insignificant. This suggests that banks with more diversified board characteristics are associated with lower bank risk. The control variables show that increasing ROA and board size increases the *lnZ-score*, but that increasing leverage ratio lowers the *lnZ-score*.

Model 3 and Model 4 report the regression results of *Volatility* on *Board diversity*. Model 4 includes control variables. *Board diversity* in both models is negatively and statistically significant, which is consistent with the results of Model 1 and Model 2 — board diversity lowers bank risk. These results suggest that board diversity has a positive effect on banks' risk. The board of Chinese banks usually consists of between 10 and 20 members, including executive directors and independent directors, and they are of different genders, ages, and work backgrounds. They are able to consider issues from multiple perspectives when making board decisions, maintaining board independence. In particular, the board has a complete set of appointment procedures and management incentives, which can effectively avoid the agency problem, nepotism between board members, and management for their own interests. For example, when a bank's strategy department makes a senior management appointment, a board with a single structure is prone to promote subordinates close to them, while a diverse board will review and assess all candidates to maximize fairness and avoid agency problems.

The control variable shows that the coefficient of bank age is slightly negative related to *Volatility*, indicating that the earlier a bank is established, the more stable its operations, the less volatile its stock, and the less likely it is to default. R-squared in these four models are over 0.4, which means the model has a high level of fit with the data.

[Inserting in Table 3.3]

[Inserting in Table 3.4]

Table 3.4 reports the results of the relationship between supervisory board diversity and bank risk. The coefficient of supervisory board diversity is only negative and significant in Model 3. It confirms the results that a bank with a more diverse boardroom has lower risk.

We next divide our samples into large and small banks according to asset size. We define large banks as those with assets of over 4.33 trillion CNY and small banks as those with assets below 4.33 trillion CNY. The results are shown in Table 5 and 6.

In Table 3.5, Models 1 to 4 are the regressions for large banks and Models 5 to 8 are regressions for small banks. However, none of the coefficients of *Board diversity* is statistically significant for large banks. For small banks, the coefficient of *Board diversity* is positively and statistically significant associated to the *lnZ-score*, and negatively related to *Volatility*. This suggests small banks with more diversified board characteristics could have lower bank risk compared to large banks. This is in fact the current situation. Big banks have grown over a long period of time and have stable profitability and risk control capabilities. At the same time, different large banks will adopt different strategies. Banks that adopt aggressive expansion strategies may increase bank risk, while banks that adopt conservative strategies may reduce bank risk. Therefore, board diversity has relatively little impact on bank risk. On the other hand, small banks pay more attention to business development and risk control. The board will consider the candidates' ability and professionalism more comprehensively when appointing management so as to avoid managers' aggressive expansion strategy in pursuit of their own interests and performance, which may lead to greater exposure to risk. Bank growth is favored through board decisions. Board diversity permits a wide range of perspectives and this helps increase the bank's profitability while reducing risk.

However, the coefficients of supervisory board diversity are all statistically significant for large banks in Table 3.6, while none are significant for small banks, which indicates that the supervisory boards of large banks are more sophisticated than those of small banks. Large banks have more diverse and complex businesses and therefore place higher demands on supervision. The diversity of the supervisory board enables supervision and control of the bank from all aspects of supervision and risk exposures.

[Inserting in Table 3.5]

[Inserting in Table 3.6]

3.5. Robustness tests

In this section, we discuss the main results of the robustness tests, including the effect of each component of board diversity on bank risk, political effect, and the effect of board diversity on the risk of peer financial institution.

3.5.1. Univariate analysis

We first examine the effect of each component of board diversity on bank risk. Table 3.7 shows the main results. We estimate the relationship between *lnZ-score* and the fraction of female, the standard deviation of age of board members, *1-HHI_Education* and *1-HHI_Expertise* in Panel A. And we next examine the relationship between the *Volatility* of weekly stock returns and each component in Panel B.

As shown in Table 3.7, the fraction of females on the board has a statistically insignificant relation with both *lnZ-score* and *Volatility.* This is because China has long been a patriarchal society and the idea that "men work outside the home and women take care of the family" is deeply rooted. Men are still the dominant influence, be it in politics, economics, law, finance or the military. Although women's voices have been given growing attention in recent years, their influence is still limited.

The coefficient of *Std_Age* is positively and significantly associated to *lnZ-score* in Model 4 in Panel A, and negatively and significantly associated to *Volatility* in Model 3 in Panel B. This suggests that the increased standard deviation of age lowers bank risk. This is probably because when the age of board members is more varied, the board is able to listen to a wide range of opinions and decisions from different age groups and, therefore, bank risk is lower. At the same time, the results of the average board age in Panel B show a positive and significant effect on *Volatility*. This suggests that an increase of one year in the average board age raises *Volatility* from 0.021 to 0.027. This is because the average age of the board of directors in the Chinese banking industry is around 54 years old (shows in Table 2). An increase in the average age leads to more conservative decisions being taken by the board, which affects profitability levels and causes stock volatility.

1-HHI_Expertise is positively correlated to *lnZ-score* in Model 7 and Model 8 in Panel A, and *1-HHI_Education* is negatively correlated to *Volatility* in Model 5 and Model 6 in Panel B. This suggests that the more diversified education and financial expertise, the lower the bank's risk is.

Moreover, the control variables also exhibit some economic significance. In Panel A, *lnBoardSize* has a positive correlation with *lnZ-score*, ROA has a positive and significant effect and Leverage ratio has a negative and significant effect on *lnZ-score*. This suggests that a bank with a relatively large board, better profitability and less liability has lower bank risk. In Panel B, *lnBankAge* has a negative and significant effect on *Volatility*, indicating that the longer the bank has been in existence, the more stable it is.

[Inserting in Table 3.7]

3.5.2. Political effect

We next examine the political effect on bank risk. We measure political variable as the fraction of board members who works for government department or whose former job was in government department. The results are shown in Table 3.8. The coefficients of *Pct_Goverment* are positive on *lnZ-score* and negative on *Volatility*, but they are all insignificant. It indicates that there is very little political effect in banks. The possible reason for this is that usually government agencies enter the board of banks only as independent directors and play a supervisory role on the board and bank operations, which has little influence bank's decision making. Therefore the effect on bank risk generation is very small.

[Inserting in Table 3.8]

3.5.3. Quantile regression analysis

In this section, following Gulamhussen et al. (2012), we estimate quantile regression by assessing whether the relationship between bank risk and board diversity, as well as the relationship between bank risk and each univariate factor, is a linear or non-linear relation. If there is a non-linear relation, we will figure out whether bank risk varies with the level of board diversity, female, age, education background and financial expertise, as regular regressions merely provide a grand summary of the averages of the distributions of the explanatory variables, yielding an incomplete picture of the actual relations. We separate our samples into four groups and test whether each bank, or at least a set of banks that fall within the same quantile, has a different impact on bank risk. Table 3.9 present the results of quantile regressions of board diversity and univariate factors. The results of quantile regressions with stock volatility as the explanatory variable are not presented because when we use volatility as the dependent variable, it results in smaller observations for each groups, and most results are shown statistically insignificant.

[Inserting in Table 3.9]

The results show that board diversity (in Panel A) and the standard deviation of age (in Panel C) are statistically insignificant for all quantile regressions. Panel B shows that more diversity in terms of female leads to more risk. It is consistent with critical mass theory that predicts a minimum level of diversity after which can be impactful. Both Panel D and E show that for low levels of diversity in terms of education background and financial expertise there is an increase in risk, while for high levels there is a decrease. In order to get a more intuitive view for the relationship between bank risk and the different independent variables, we substituted the coefficients obtained from the quantile regressions back into the equation to calculate the predicted Z-score and make graphs at 95% confidence level. Figure 3.1 depicts an inverse U-shaped relation between bank risk and board diversity. The non-linear relation suggests that the effect of board diversity across the spectrum of Z-score is not constant. A low level of board diversity can lead to an over-centralization of power, in which case the strategies made are prone to increase the bank's risk due to blind confidence without fully considering the bank's actual situation. A high level of board diversity can lead to inefficiency due to long discussion time and complicated decision-making process, thus increasing the bank's risk.

Figure 3.2 to Figure 3.5 depict the relation between bank risk and univariate factors. Demographic factors (female and age) have an inverted U-shaped relation, while cognitive factors (education background and financial expertise) have a U-shaped relation. After 20% to 25% female in the boardroom may lead to higher risk in Chinese commercial banks. The optimal point of the standard deviation of age is about 9. Lower or over 9 may also lead to higher risk. This indicates that high level and low level of diversity in terms of demographic factors can cause bank risk to rise. The possible reason for this is that a high level of diversity in such characteristics can lead to problems such as long decision-making time, inefficient decision-making and complex decision-making processes, while a low level of diversity can lead to problems such as centralization of power and incomplete consideration of issues, resulting in an increase in bank risk. On the contrary, the minimum level of diversity in terms of education background and financial expertise are about 0.65 and 0.65 respectively, which indicates that low level and high level of diversity decrease bank risk. The possible reason for this is that a low level of diversity in terms of cognitive factors will analyze the problem from a single or professional perspective, and such decisions tend to be more efficient, which is efficiency oriented, while a high level of diversity will analyze the problem from multiple perspectives, and such decisions are more specialized and cover a wider range of areas, which is multi-dimensional specialization oriented.

[Inserting in Figure 3.1]
[Inserting in Figure 3.2]
[Inserting in Figure 3.3]
[Inserting in Figure 3.4]
[Inserting in Figure 3.5]

3.5.4. Board diversity of peer investment banking

Thus far, we have addressed the relation between board diversity and risk only for commercial banks. In this section, we expand our samples to include the financial institutions of investment banking and brokerage services. The list of investment banking and brokerage comes from Eastmoney. We extract the weekly stock returns from Refinitiv Eikon and board characteristics from the annual reports of each financial institution. Finally, we have 408 observations of commercial banks and 199 observations for investment banking and brokerage services.

[Inserting in Table 3.10]

Table 3.10 reports the regression results. The dependent variable of Model 1 and Model 2 is *lnZ-score*, and the dependent variable of Model 3 and Model 4 is *Volatility*. The coefficients of *Board diversity* in Model 1 and Model 2 are still positive and statistically significant, which means that a financial institution with a more diversified board is associated with less risk. This reinforces our earlier conclusion in Table 3.3. However, the effect of *Board diversity* becomes insignificant in Models 3 and 4. The main reason for this is that financial institutions with investment banking and brokerage services are more specialized than banks. In China, people use the investment banking and brokerage industry as a weathervane of the stock market. During bull years, investment banking and brokerage services stocks start by rising substantially and then quickly fall when they enter a bear market, making them more vulnerable to risk and emotional trading controls.

Second, we only add data for the period from 2017 to 2021. The Chinese stock market was affected by many international events in this period, such as the US-China trade war and the Covid-19 virus when it experiencing several bear-bull-bear transitions. Adding the samples of the investment banking and brokerage services amplifies the effect of international events on financial institutions. In comparison, the impact of board diversification seems insignificant.

3.5.5. Reverse causality issue

In our previous analysis, we find that a diverse board brings lower risk. However, there is concern that a bank with lower risk may attract more directors or board members with a diverse background than a bank with higher risk. Therefore, we may be facing a reverse causality issue. To check and address reverse causality, we first add several covariates to control our findings. Second, we used change and reverse change tests in line with Aggarwal et al. (2011) and Jebran et al. (2020). We assume that if board diversity affects a bank's future risk, as board diversity increases over time, bank risk decreases correspondingly. Inversely, we estimate whether a bank with lower future risk attracts more directors and board members with a diverse background.

Model 1 in Table 3.11 shows the results for the regression of the change of volatility *(△Volatility)* as the dependent variable, and the change of board diversity *(△Board diversity)* as the explanatory variable. We adopt *△Volatility* from *T-1* to *T* as the dependent variable, *△Board diversity* from *T-2* to *T-1* as the explanatory variable, and also changed the control variables from *T-2* to *T-1*. As shown in Model 1, there is a negative relation between *△Volatility* and *△Board diversity*. The coefficient of *△Board diversity* is negative and significant at the 10% level.

To further address reverse causality issues, we conduct the changes regression analysis in the reverse direction. We want to determine whether a bank with less future risk attracts directors and board members with a diverse background. We use *△Board diversity* from *T-1* to *T* as the dependent variable, and *△Volatility* from *T-2* to *T-1* as the explanatory variable. Model 2 in Table 3.11 shows the results of reverse change test. The coefficient of *△Volatility* is statistically insignificant. This evidence confirms our previous results that a bank with a more diverse board has lower volatility of its stock returns, but a bank with lower risk does not attract more directors with a diverse background than a bank with higher risk.

[Inserting in Table 3.11]

In further analysis of causality, we find that *△Board diversity* and *△lnZscore* detect reverse causality issues (results are not shown in the Table). Hence, we explore an instrument variable. The instrument variable should be correlated with *Board diversity* but not with *lnZscore*. However, it is difficult to find an effective instrument in this case because the instrument variables most correlated with our endogenous variable, such as board size and asset, are already included in our regression.

3.5.6. Instrumental variable

In this section we try to find an instrument variable. The selected instrumental variable should be correlated with the board diversity but uncorrelated with bank risk. Adam and Ferreira (2009) adopt the fraction of male directors with board connections to female directors could be a valid instrument for the fraction of female directors, which is similar to the studies of Gulamhussen and Santa (2015). In our studies, our independent variable is board diversity that considering fraction of female, age, education background and financial expertise. Hence, we hypothesize that the fraction of board members with board connections to other companies could be a valid instrument for board diversity. We measure the fraction of board members who are also board members in other companies as instrumental variable. The results are reported in Table 3.12.

[Inserting in Table 3.12]

As shown in Model 2 in Table 3.12, with considering the instrumental variable, the coefficient of board diversity turns to positively significant, which confirms with previous results — a bank with a more diverse boardroom has a lower risk, while it is insignificant to Model 3. The possible reason is that Z-score measures risk-taking which is internal to the bank, while volatility measures risk which is external to the bank.

3.5.7. Sample selection bias

We further address the potential sample selection bias. The method we use is the Heckman's two-stage correction model (Heckman, 1979). Our initial samples are the listed Chinese commercial banks that are likely to comprise of larger banks with a more diverse board than the average. In the first stage, we use the probit regression with the dependent variable *LargeBoardDiv* equal to one if board diversity is greater than the median of board diversit*y,* similar to the method employed by Harjoto et al. (2018). The independent variables are DualBoard, log of asset, log of firm age, log of operating revenue and ROA, in line with Hillman et al. (2007) and Gul et al. (2011). They argue that older and more profitable banks are is more likely to be more diverse. Diversified banks are probably in greater need of varied perspectives. In the second stage regression, we use the fitted value of board diversity from the first stage to examine the impact of board diversity on bank risk. Table 3.13 reports the results. The result of the fitted value of board diversity in Model 2 in the second stage is statistically significant at the level of 5% and lambda is significant at the level 1%, which confirms our previous results. The VIF of imr is 6.46, mean VIF is 2.81, far from 10. However, the result of the fitted value of board diversity in Model 3 is insignificant. Again, the possible reason is the different measurement of bank risk.

[Inserting in Table 3.13]

3.6. Discussion

This paper discusses the impact of board diversity on bank risk. In fact, many studies also focus on the bank performance. Ozdemir (2020) examines the relationship between board diversity and firm performance in the U.S. tourism sector and find that board diversity has a positive effect on financial performance. Vafaei et al. (2015) examined the impact of a single factor of the board diversityon firm performance and find that there is a positive relationship between board diversity and financial performance with controlling for firm-specific and governance-related factors. Miller and Triana (2009) also find the evidence for supporting the positive effect of board diversity on performance. Bernile et al. (2018) find that greater board diversity leads to lower volatility and better performance. Why do we not explore the relationship between board diversity and bank performance?

First, we know that bank risk is often intrinsically linked to bank performance. For example, profitable banks tend to be less risky while less profitable banks are accompanied by high risk. We use bank performance (ROA) as a control variable. Second, banks can take the risk as long as they don't go bankrupt. Bank risk is always been discussed. With the frequent occurrence of unexpected events such as the US-China trade war and pandemic viruses in recent years, bank risk has increased. Various countries have adopted monetary policies such as interest rate cuts and fiscal policies such as subsidies to avoid these risks from becoming systemic risks for banks. Bank management has also responded to this by, for example, suspending or delaying mortgage repayments for homebuyers during Covid-19 in China. In the future, we will increasingly see banks increasing their performance to the extent they can afford to do so, rather than inflate their risks while pursuing profits.

Moreover, many scholars focus on executive directors and independent directors in board. Executive directors are those who are responsible for the business of the company in addition to participating in the operational decisions of the board of directors. Independent directors are directors who are independent of the company's shareholders and make independent judgments about the company's affairs. We observe that independent directors of Chinese commercial banks are usually composed of university professors, independent directors or executives of other companies, and government agencies. In our study, we also separately tested the effect of the percentage of independent board members on bank risk, and the results (not reported in the table) show that the percentage of independent board members has a positive effect on the *lnZscore*, i.e., the higher the number of independent board members, the more the board can maintain its independence and lower the bank risk.

3.7. Conclusion

Many scholars conduct research on the impact of different aspects of diversity on bank risk. This paper develops and uses a new variable of board diversity to evaluate the impact on Chinese bank risk in a quantitative way. Specifically, we measure board diversity by normalizing the factors of the fraction of females on the board, the standard deviation of age of board members, HHI index of education background, and HHI index of financial expertise. Our OLS results suggest that a bank with more diversified board can have lower risk. This result is particularly marked for small banks. It is consistent with our agency hypothesis — a more diverse board can avoid agency problems between management and shareholders, thus reducing bank risk. Board diversity avoids nepotism between board members and management when appointing management. The selection and appointment of management is more focused on the individual competencies of management in order to more effectively increase bank performance and manage risk. At the same time, the compensation incentive criteria for managers will allow management to better serve the bank. Additionally, we use the same method to calculate supervisory board diversity. The results show that a bank with more diverse supervisory board will reduce bank risk slightly. And this result is obviously for large banks.

We then use robustness tests to estimate the impact of univariate factors on bank risk. We find that female presence on the board is not significant for bank risk, while diversity of age, educational background and financial expertise can reduce bank risk to varying degrees. Our paper also contributes by quantifying the government effect, using the percentage of board members assigned by the government or whose previous job was in a government department. However, our results show that this has no significant effect on bank risk. Our analysis finds that board members from government agencies only play a supervisory role on the board and in bank operations and therefore have little influence on bank decision-making. We also estimate quantile regressions, and find demographic factors (female and age) have an inverted U-shaped relation, while cognitive factors (education background and financial expertise) have a U-shaped relation. In addition, we extend our samples by adding financial institutions with investment banking and brokerage services to validate the previous main findings. We find that board diversity is still significant on lnZ-score, which reinforces our findings — board diversity is a good way of reducing the risk of financial institutions. Finally, we adopt the fraction of board members who are also the board members in other companies as the instrumental variable. The results are consistent with our findings.

The results of this paper also have implications for practice. From the perspective of bank governance, care should be taken to diversify and consider different characteristics of board members when building the board team; for example, there should be more female and younger members, as well as industry experts as independent directors, so that different voices can be heard and the board's independence maintained. From the perspective of regulator, regulators should strengthen their ties with bank boards and build a new regulatory relationship based on trust. The Silicon Valley Bank incident has taught us that loosening regulatory requirements for banks can easily lead to a relaxation of internal controls over bank risk, causing irreversible losses to the bank. Therefore, regulators need to engage in dialogue with boards of directors to assess bank strategies, business models and risks, to identify problems and address them.

However, our paper has some limitations. We only focus on the listed commercial banks; over 3000 non-listed commercial banks are not included in the study. In addition, we do not know if the results would remain the same if we introduced a new component to board diversity, such as the tenure, or whether board diversity would have the same impact on the risk of other industries in China. These questions will be the focus of future research.

Table 3.1: Variable Definitions.

This table provides variable names, definitions, and data sources.

Variables	Definition	Source
Dependent variable:		
lnZ-score	The logarithm of Z-score, Z-score calculated as (ROA+Equity/Asset)/Stdv.ROA.	Calculate
Volatility	Standard deviation of weekly stock rate of returns.	Calculate; Refinitiv Eikon
Independent variable:		
Board diversity (Supervisory board)	Normalized fraction of female + normalized standard deviation of age – normalized HHI of education – normalized HHI of financial expertise.	Calculate; Annual reports
Control variables:		
lnAsset	The logarithm of asset.	Annual reports
lnBoardSize	The logarithm of board size.	Annual reports
lnBoardAge	The logarithm of board average age.	Annual reports
lnBankAge	The logarithm of bank age.	Calculate; Annual reports
ROA	Net income/asset.	Calculate; Annual reports
Leverage ratio	Total debt/total equity.	Calculate; Annual reports
Robustness tests:		
Pct_Female	The fraction of female board members.	Calculate; Annual reports
Std_Age	Standard deviation of board members' age.	Calculate; Annual reports
HHI_Education	Herfindahl concentration index of different education background with 4 categories: undergraduate, bachelor, master and PhD or above.	Calculate; Annual reports
HHI_Expertise	Herfindahl concentration index of financial working experience with 5 categories: (1) has held a board member position at banking institution or the former job was at a banking institution, (2) has held a board member position at non-banking financial institution or the former job was at a non-banking institution, (3) the former job was related to finance but at non-financial institution (e.g. CFO, accountant treasurer), (4) holds an academic position in a related field (e.g. assistant Professor, Professor of finance, economics and accounting), (5) no finance related experience.	Calculate; Annual reports
Pct_Government	The fraction of employees assigned by government or whose former job was in government department.	Calculate; Annual reports
LargeBoardDiversity	A dummy variable equal to one if board diversity is greater than the median of board diversity	Calculate
lnOperatingRevenue	The logarithm of operating revenue	Annual reports
Others:		
Stdv. ROA	The volatility of ROA by using the rolling window of 3 years.	Calculate; Annual reports
Time FE	Time fixed effect	
Bank FE	Bank fixed effect	

Table 3.2: Summary statistics.

This table shows summary statistics for the sample.

Variables	N	Mean	Std.dev.	Min.	Max.	Median
Panel A						
lnZ-score	408	0.22	0.98	-4.10	3.09	0.27
Volatility	330	0.02	0.01	0.00	0.05	0.01
Board diversity	408	1.16e-15	2.01	-8.64	6.17	-0.07
Pct_Female	408	0.14	0.10	0	0.5	0.13
Std_Age	408	6.51	1.50	2.75	11.51	6.40
HHI_Education	408	0.39	0.07	0.25	0.63	0.38
HHI_Expertise	408	0.33	0.08	0.20	0.69	0.31
Asset	408	4.33e+12	6.64e+12	7.55e+10	3.52e+13	1.32e+12
lnAsset	408	28.04	1.53	25.05	31.19	27.91
BoardSize	408	14.31	2.33	8	19	15
lnBoardSize	408	2.64	0.17	2.08	2.94	2.71
BoardAge	408	54.56	2.57	47.18	60.81	54.66
lnBoardAge	408	4.00	0.05	3.85	4.11	4.00
BankAge	408	29.35	23.64	3	113	22
lnBankAge	408	3.17	0.60	1.10	4.73	3.09
ROA	408	0.01	0.00	-0.01	0.09	0.01
StdROA	408	0.13	0.41	0.00	4.77	0.06
Leverage ratio	408	13.68	3.80	7.26	44.37	12.79
Pct_Government	408	0.18	0.15	0	0.67	0.15
Panel B		N(Pct_Female)	N(Std_Age)	N(HHI_Edu)	N(HHI_Exp)	
N(Pct_Female)		1.00				
N(Std_Age)		0.02	1.00			
N(HHI_Education)		0.12	-0.21	1.00		
N(HHI_Expertise)		0.02	0.12	0.07	1.00	
Board diversity		0.04	0.55	-0.57	-0.46	

Table 3.3: Board diversity and bank risk.

This table reports OLS regressions of the relation between the board diversity and risks over the period 2006–2021. The board diversity is normalized by the mean and standard deviation of each component. The dependent variable of Model 1 and 2 is lnZ-score, Model 2 includes the control variables. The dependent variable of Model 3 and 4 is the standard deviation of weekly stock returns, Model 4 includes the control variables. All regressions include bank fixed effects and time fixed effects. Robust t-statistics are in parentheses. *, **, *** denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Dependent variable:	lnZ-score		Volatility	
Board diversity	0.0452*	0.0438	-0.0006***	-0.0005***
	(1.68)	(1.63)	(-3.17)	(-2.73)
lnAsset		0.3361		0.0022
		(1.35)		(0.94)
lnBoardSize		1.1719***		-0.0035
		(2.96)		(-1.14)
lnBoardAge		-1.3760		0.0156
		(-0.89)		(1.25)
lnBankAge		-0.0284		-0.0095*
		(-0.05)		(-1.90)
ROA		23.1678**		0.1601*
		(2.07)		(1.82)
Leverage ratio		-0.0345**		0.0001
		(-2.23)		(0.77)
Bank fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Observations	408	408	330	330
R-squared	0.4147	0.4490	0.5397	0.5542

Table 3.4: Supervisory board diversity and bank risk.

This table reports OLS regressions of the relation between the supervisory board diversity and risk over the period 2006–2021. The supervisory board diversity is normalized by the mean and standard deviation of each component. The dependent variable of Models 1 and 2 is lnZ-score, Model 2 includes the control variables. The dependent variable of Models 3 and 4 is the standard deviation of weekly stock returns, Model 4 includes the control variables. All regressions include bank fixed effects and time fixed effects. Robust t-statistics are in parentheses. ∗, ∗∗, ∗∗∗ denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Dependent variable:	lnZ-score		Volatility	
Supervisory board	0.0167	0.0179	-0.0004*	-0.0003
	(0.61)	(0.65)	(-1.85)	(-1.51)
lnAsset		0.3243		0.0026
		(1.19)		(1.12)
lnBoardSize		1.1595***		-0.0031
		(2.92)		(-1.00)
lnBoardAge		-1.6561		0.0212*
		(-1.07)		(0.87)
lnBankAge		-0.0240		-0.0099**
		(-0.04)		(-1.97)
ROA		23.1225**		0.1632*
		(2.06)		(1.84)
Leverage ratio		-0.0341**		0.0002
		(-2.19)		(0.96)
Bank fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Observations	408	408	330	330
R-squared	0.4104	0.4453	0.5283	0.5453

Table 3.5: Board diversity and bank risk for large and small banks.

This table reports OLS regressions of the relation between the board diversity and risk over the period 2006–2021 of subsample large and small banks. The board diversity is normalized by the mean and standard deviation of each component. Models 1 to 4 are for large banks. The dependent variable of Models 1 and 2 is lnZ-score, Model 2 includes the control variables. The dependent variable of Models 3 and 4 is the standard deviation of weekly stock returns, Model 4 includes the control variables. Models 5 to 8 are for small banks. The dependent variable of Models 5 and 6 is lnZ-score, Model 6 includes the control variables. The dependent variable of Models 7 and 8 is the standard deviation of weekly stock returns, Model 8 includes the control variables. All regressions include bank fixed effects and time fixed effects. Robust t-statistics are in parentheses. ∗, ∗∗, ∗∗∗ denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Large				Small			
Dependent variable:	lnZ-score		Volatility		lnZ-score		Volatility	
Board diversity	-0.0022	0.0225	-0.0002	-0.0002	0.0815**	0.0482	-	-
	(-0.06)	(0.53)	(-1.13)	(-0.82)	(2.06)	(1.22)	0.0008***	0.0008**
							(-2.60)	(-2.33)
lnAsset		-0.3756		0.0073		1.0882**		0.0043
		(-0.22)		(0.77)		(2.53)		(1.09)
lnBoardSize		0.5736		0.0006		1.5318***		-0.0033
		(0.93)		(0.17)		(2.83)		(-0.73)
lnBoardAge		5.3752*		0.0478***		-1.9942		0.0167
		(1.85)		(3.19)		(-1.00)		(0.88)
lnBankAge		-2.8712		-0.0108		0.7661		-0.0047
		(-1.63)		(-1.02)		(0.89)		(-0.53)
ROA		230.3049**		1.3112***		41.1949***		0.2018
		(2.62)		(2.80)		(2.86)		(1.57)
Leverage ratio		-0.0754		-0.0015**		-0.0557***		0.0001
		(-1.13)		(-2.51)		(-2.76)		(0.40)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	114	114	104	104	294	294	226	226
R-squared	0.7202	0.7702	0.8201	0.8803	0.3003	0.3634	0.4633	0.4801

Table 3.6: Supervisory board diversity and bank risk for large and small banks.

This table reports OLS regressions of the relation between the supervisory board diversity and risk over the period 2006–2021 of subsample large and small banks. The supervisory board diversity is normalized by the mean and standard deviation of each component. Models 1 to 4 are for large banks. The dependent variable of Models 1 and 2 is lnZ-score, Model 2 includes the control variables. The dependent variable of Models 3 and 4 is the standard deviation of weekly stock returns, Model 4 includes the control variables. Models 5 to 8 are for small banks. The dependent variable of Models 5 and 6 is lnZ-score, Model 6 includes the control variables. The dependent variable of Models 7 and 8 is the standard deviation of weekly stock returns, Model 8 includes the control variables. All regressions include bank fixed effects and time fixed effects. Robust t-statistics are in parentheses. ∗, ∗∗, ∗∗∗ denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Large				Small			
Dependent variable:	lnZ-score		Volatility		lnZ-score		Volatility	
Supervisory board	0.1027***	0.0873***	-0.0005***	-0.0005***	-0.0180	-0.0247	-0.0004	-0.0003
	(-0.06)	(2.73)	(-2.84)	(-3.40)	(-0.45)	(-0.61)	(-1.08)	(-0.75)
lnAsset		-0.7779		0.0103		1.1863***		0.0030
		(-0.47)		(1.16)		(2.76)		(0.75)
lnBoardSize		0.5159		0.0001		1.6219***		-0.0049
		(0.88)		(0.14)		(3.02)		(-1.07)
lnBoardAge		5.7644**		0.0440***		-2.5476		0.0252
		(2.20)		(3.35)		(-1.26)		(1.31)
lnBankAge		-2.6393		-0.0135		0.7966		-0.0027
		(-1.66)		(-1.38)		(0.92)		(-0.30)
ROA		207.5339**		1.4021***		44.6732***		0.1502
		(2.51)		(3.33)		(3.12)		(1.17)
Leverage ratio		-0.0540		-0.0016***		-0.0546***		0.0001
		(-0.84)		(-2.83)		(-2.69)		(0.56)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	114	114	104	104	294	294	226	226
R-squared	0.7505	0.7893	0.8343	0.8959	0.2878	0.3602	0.4453	0.4642

Table 3.7: Univariate and bank risk.

This table reports OLS regressions of the relation between the univariate factor and risk over the period 2006–2021. The dependent variable is lnZ-score in Panel A and Volatility of weekly stock returns in Panel B. Models 2,4,6 and 8 include the control variables. All regressions include bank fixed effects and time fixed effects. Robust t-statistics are in parentheses. ∗, ∗∗, ∗∗∗ denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A					lnZ-score			
Pct_Female	-0.4311	-0.2458						
	(-0.80)	(-0.43)						
Std_Age			0.0539	0.0689*				
			(1.49)	(1.88)				
1-HHI_Education					0.5089	0.1557		
					(0.63)	(0.19)		
1-HHI_Expertise							1.5124**	1.2291*
							(2.20)	(1.77)
lnAsset		0.3528		0.4422		0.3458		0.2978
		(1.29)		(1.60)		(1.26)		(1.09)
lnBoardSize		1.1367***		1.1222***		1.1557***		1.1848***
		(2.82)		(2.83)		(2.89)		(2.99)
lnBoardAge		-1.9625		-1.6121		-1.8316		-1.3141
		(-1.24)		(-1.06)		(-1.18)		(-0.85)
lnBankAge		0.0505		-0.0103		0.0180		0.1077
		(0.09)		(-0.02)		(0.03)		(0.19)
ROA		23.8814**		25.9537**		23.5246**		21.7483*
		(2.12)		(2.31)		(2.09)		(1.94)
Leverage ratio		-0.0323**		-0.0382**		-0.0329		-0.0304*
		(-2.06)		(-2.44)		(-2.11)		(-1.95)
Observations	408	408	408	408	408	408	408	408

(Continue Table 3.7)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel B					Volatility			
Pct_Female	-0.0041	-0.0032						
	(-1.05)	(-0.77)						
Std_Age			-0.0005*	-0.0004				
			(-1.70)	(-1.35)				
1-HHI_Education					-0.0137**	-0.0141**		
					(-2.30)	(-2.29)		
1-HHI_Expertise							-0.0070	-0.0062
							(-1.39)	(-1.20)
lnAsset		0.0027		0.0018		0.0015		0.0026
		(1.11)		(0.76)		(0.64)		(1.10)
lnBoardSize		-0.0035		-0.0029		-0.0026		-0.0034
		(-1.12)		(0.96)		(-0.84)		(-1.10)
lnBoardAge		0.0218*		0.0219*		0.0268**		0.0210*
		(1.72)		(1.78)		(2.21)		(1.68)
lnBankAge		-0.0102**		-0.0104**		-0.0099**		-0.0109**
		(-2.02)		(-2.08)		(-1.98)		(-2.19)
ROA		0.1657*		0.1419		0.1479*		0.1684*
		(1.85)		(1.58)		(1.67)		(1.89)
Leverage ratio		0.0002		0.0002		0.0001		0.0001
		(0.93)		(1.04)		(0.55)		(0.74)
Observations	330	330	330	330	330	330	330	330
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3.8: Political effect and bank risk.

This table reports OLS regressions of the relation between the fraction of board members whose position or former job is in a government department and risk over the period 2006–2021. The dependent variable of Models 1 and 2 is lnZ-score, Model 2 includes the control variables. The dependent variable of Models 3 and 4 is the standard deviation of weekly stock returns, Model 4 includes the control variables. All regressions include bank fixed effects and time fixed effects. Robust t-statistics are in parentheses. ∗, ∗∗, ∗∗∗ denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Dependent variable:	lnZ-score		Volatility	
Pct_Government	0.2739	0.4598	-0.0009	-0.0010
	(0.42)	(0.71)	(-0.19)	(0.20)
lnAsset		0.3492		0.0023
		(1.28)		(0.99)
lnBoardSize		1.1913***		-0.0031
		(2.98)		(-1.00)
lnBoardAge		-1.8759		0.0242**
		(-1.22)		(1.97)
lnBankAge		-0.0142		-0.0108**
		(-0.03)		(-2.13)
ROA		23.4991**		0.1580*
		(2.09)		(1.77)
Leverage ratio		-0.0328**		0.0002
		(-2.11)		(0.90)
Bank fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Observations	408	408	330	330
R-squared	0.4101	0.4454	0.5222	0.5414

Table 3.9: Quantile regressions analysis.

This table reports quantile regressions of the relation between the diversity and risk over the period 2006–2021. The dependent variable of lnZ-score. Independent variable is board diversity, percentage of female, standard deviation of age, 1-HHI Education, 1-HHI Expertise divided into four quantiles in Panel A to Panel E, respectively. Robust t-statistics are in parentheses. $*$, $**$, $***$ denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
	25%	50%	75%	100%
Panel A	lnZ-score			
Board diversity	0.1000	0.0838	0.2481	0.1138
	(0.99)	(0.36)	(1.44)	(0.99)
lnAsset	0.3073***	0.1542**	0.0493	-0.1323
	(2.93)	(2.02)	(0.61)	(-1.21)
lnBoardSize	1.1199	-0.4460	-0.3535	-0.8644
	(1.45)	(-0.84)	(-0.79)	(-1.30)
lnBoardAge	-2.1251	2.9792	4.6698*	1.9688
	(-0.64)	(1.44)	(1.95)	(0.92)
lnBankAge	-0.3246	-0.3303**	-0.0421***	0.6905***
	(-1.22)	(-2.07)	(-0.30)	(2.78)
ROA	2.1051	31.5161	-61.7178	-10.0786
	(0.16)	(1.03)	(-1.62)	(-0.27)
Leverage ratio	-0.1539***	-0.0849***	-0.1417***	-0.0112
	(-4.30)	(-3.39)	(-4.95)	(-0.46)
Observations	102	102	102	102

(Continue Table 3.9)

	(1)	(2)	(3)	(4)
	25%	50%	75%	100%
Panel B		lnZ-score		
Pct_Female	1.5062	1.0412	-1.9403	-3.8276***
	(0.39)	(0.16)	(-0.43)	(-2.74)
lnAsset	0.09425	0.0754	0.1581*	-0.1057
	(0.92)	(0.86)	(1.71)	(-1.17)
lnBoardSize	0.6120	0.4552	-0.1411	-1.1724**
	(0.79)	(0.60)	(-0.20)	(-2.25)
lnBoardAge	4.0013	-2.3167	-2.5491	4.7942**
	(1.28)	(-0.85)	(-0.99)	(2.18)
lnBankAge	-0.2804	0.3805**	-0.4423**	0.2175
	(-1.29)	(2.15)	(-2.18)	(0.96)
ROA	-15.1181	-9.1754	110.4248***	-5.4859
	(-1.19)	(-0.18)	(3.33)	(-0.17)
Leverage ratio	-0.0969***	-0.1341***	-0.0905***	-0.0429**
	(-3.32)	(-3.52)	(-2.95)	(-2.17)
Observations	114	81	116	122
Panel C	lnZ-score			
Std_Age	0.0634	-0.4223	0.1621	0.0252
	(0.41)	(-1.52)	(0.61)	(0.25)
lnAsset	0.1743*	-0.0349	0.1259	-0.0015
	(1.70)	(-0.44)	(1.19)	(-0.02)
lnBoardSize	1.9137***	-0.8080	-0.1460	-1.2130**
	(3.08)	(-1.39)	(-0.22)	(-2.35)
lnBoardAge	-1.0696	0.9373	1.0902	1.6115
	(-0.34)	(0.38)	(0.36)	(0.91)
lnBankAge	-0.1935	0.0311	0.0518	0.2739*
	(-0.73)	(0.16)	(0.26)	(1.79)
ROA	-11.8128	78.2509**	-85.8142**	38.1409
	(-0.85)	(2.45)	(-2.06)	(0.233)
Leverage ratio	-0.1374***	-0.0353	-0.0544**	-0.1662***
	(-3.72)	(-1.64)	(-2.20)	(-5.48)
Observations	102	103	101	102

(Continue Table 3.9)

	(1)	(2)	(3)	(4)
	25%	50%	75%	100%
Panel D		lnZ-score		
1-HHI_Education	-5.1874**	-4.533218	6.9943	8.9545**
	(-2.26)	(-0.54)	(0.99)	(-2.26)
lnAsset	0.4019***	-0.0114	-0.0750	-0.0190
	(3.54)	(-0.16)	(-0.57)	(-0.18)
lnBoardSize	1.1710**	-1.4797***	-0.2985	1.1855**
	(2.01)	(-2.72)	(-0.57)	(1.94)
lnBoardAge	-4.8526	3.4208	3.6053*	2.4638
	(-1.42)	(1.65)	(1.79)	(1.03)
lnBankAge	-0.7384***	0.3057	-0.1822	0.9460***
	(-3.59)	(1.64)	(-1.13)	(4.10)
ROA	80.2955*	130.1964***	-24.5770**	-165.5330***
	(1.72)	(4.56)	(-4.06)	(-3.67)
Leverage ratio	-0.2210***	-0.1322***	-0.0776***	-0.0738***
	(-5.64)	(-4.03)	(-4.06)	(-2.98)
Observations	102	101	106	99
Panel E	lnZ-score			
1-HHI_Expertise	-0.6029	-14.1822***	6.5957	17.1376***
	(-2.26)	(-3.08)	(0.75)	(3.17)
lnAsset	-0.0480	0.1911**	0.1000	-0.0069
	(-0.58)	(2.54)	(0.90)	(-0.09)
lnBoardSize	-0.7929	-0.9494**	1.2706*	-0.0554
	(-1.30)	(-2.03)	(1.78)	(-0.12)
lnBoardAge	2.6382	0.7138	2.9617	-1.3676
	(1.27)	(0.39)	(1.08)	(-0.53)
lnBankAge	0.1580	-0.2556*	-0.0353	0.1504
	(0.82)	(-1.68)	(-0.18)	(0.72)
ROA	121.1181***	60.5409*	8.3650	-31.1954***
	(4.49)	(1.83)	(0.17)	(-3.16)
Leverage ratio	-0.1285***	-0.0838**	-0.1696***	-0.0559***
	(-5.38)	(-2.49)	(-4.45)	(-3.54)
Observations	99	102	105	102

Table 3.10: Board diversity and risk for financial institutions.

This table reports OLS regressions of the relation between the board diversity and risk for financial institutions, including all listed commercial banks and investment banking and brokerage services over the period 2006–2021 (the data of financial institutions with investment banking and brokerage services only from last five years). The board diversity is normalized by the mean and standard deviation of each component. The dependent variable of Models 1 and 2 is lnZ-score, Model 2 includes the control variables. The dependent variable of Models 3 and 4 is the standard deviation of weekly stock returns, Model 4 includes the control variables. All regressions include bank fixed effects and time fixed effects. Robust t-statistics are in parentheses. ∗, ∗∗, ∗∗∗ denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Dependent variable:	lnZ-score		Volatility	
Board diversity	0.0442*	0.0494**	0.0001	-0.0003
	(1.92)	(2.13)	(0.18)	(-0.95)
lnAsset		0.0356		0.0061***
		(0.24)		(3.01)
lnBoardSize		1.2328***		0.0037
		(3.48)		(0.75)
lnBoardAge		0.2870		-0.0196
		(0.23)		(-1.14)
lnBankAge		-0.1415		-0.0089
		(-0.27)		(-1.03)
ROA		23.2233***		0.0234
		(3.55)		(0.27)
Leverage ratio		-0.0181		0.0004
		(-1.19)		(1.26)
Bank fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Observations	607	607	529	529
R-squared	0.3626	0.4004	0.3311	0.3568

Table 3.11: Robustness check for change and reverse change tests.

This table reports the results for change and reverse change tests. All regressions include bank fixed effects and time fixed effects. Robust t-statistics are in parentheses. *, **, *** denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)
Dependent variable:	△Volatility$_t$	△Board diversity$_t$
△Board diversity$_{t-1}$	-0.0007*	
	(-1.92)	
△Volatility$_{t-1}$		-7.2216
		(-0.94)
△lnAsset$_{t-1}$	-0.0074	0.0849
	(-1.08)	(0.09)
△lnBoardSize$_{t-1}$	0.0025	-1.1176*
	(0.56)	(-1.76)
△lnBoardAge$_{t-1}$	-0.0269	1.8118
	(-1.37)	(0.64)
△lnBankAge$_{t-1}$	-0.0606***	-4.1068
	(-2.56)	(-1.22)
△ROA$_{t-1}$	-0.2456	3.3311
	(-1.19)	(0.11)
△Leverage ratio$_{t-1}$	0.0004	-0.0773**
	(1.52)	(-1.99)
Bank fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Observations	407	407
R-squared	0.4757	0.0551

Table 3.12: Endogeneity of total samples.

This table reports the results of the instrumental variable (IV) estimation that controls for the endogeneity of board diversity. The instrument are DualBoard and DualSupervisory, the fraction board members who are also board members in other companies. Model 1 is the first-stage regression of the IV estimation. Models 2 and 3 are the second-stage regressions of the IV estimation. F-statistic indicates whether the IV estimation is significant in the first-stage regression. All regressions include bank fixed effects and time fixed effects. Robust t-statistics are in parentheses. $*$, $**$, $***$ denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
Dependent variable:	Board diversity	lnZ-score	Volatility
	First stage	Second stage	Second stage
Board diversity		0.6552***	-0.0007
		(3.42)	(-0.51)
DualBoard	4.3975**		
	(2.04)		
lnAsset		0.4436***	-0.0017**
		(3.49)	(-2.06)
lnBoardSize		-0.5527	0.0020
		(-1.18)	(0.76)
lnBoardAge		3.0911*	-0.0089
		(1.65)	(-0.69)
lnBankAge		-0.1168	-0.0001
		(-0.79)	(-0.06)
ROA		10.0972	-0.0356
		(0.63)	(-0.41)
Leverage ratio		-0.0608***	0.0006***
		(-3.00)	(3.43)
Observations	408	408	330
F-statistic	4.15		
Endogenous test:		21.4757	0.2317
p-value		Reject at 1%	Not reject

Table 3.13: Sample selection bias tests with Heckman two-stage method.

This table reports the results of the Heckman two-stage method. In the first stage in Panel A, the dependent variable is the dummy variable equal to one if board diversity is greater than the median of board diversity. In the second stage in Panel B, we use the fitted value of board diversity from the first stage in the second stage regression to examine the impact of board diversity on bank risk. Robust t-statistics are in parentheses. *, **, *** denote significance at 10%, 5%, and 1%, respectively.

	(1)	
Panel A: First stage	Large Board diversity	
DualBoard	0.3348	
	(0.23)	
lnAsset	-2.4311***	
	(-4.48)	
lnBankAge	0.2688**	
	(1.90)	
lnOperatingRevenue	1.9505***	
	(4.04)	
ROA	-84.0866***	
	(-3.92)	
	(2)	(3)
Panel B: Second stage	lnZ-score	Volatility
Board diversity	0.0603**	-0.0001
	(2.26)	(-0.44)
lnAsset	0.1680	-0.007
	(0.62)	(-1.03)
lnBoardSize	0.9512**	0.0016
	(2.42)	(0.65)
lnBoardAge	-1.1332	-0.0046
	(-0.75)	(-0.43)
lnBankAge	0.1847	-0.0004
	(0.33)	(-0.46)
ROA	7.1686	0.0121
	(0.61)	(0.15)
Leverage ratio	-0.0424***	0.0006***
	(-2.77)	(3.93)
imr (lambda)	1.5499***	-0.0027
	(3.84)	(-1.12)
Observations	408	330
F-stat	8.93***	6.73***
R-squared	0.1518	0.1437

Figure 3.1. Graphical display of bank risk (predicted Z-score) across spectrum of board diversity.

The dependent variable is predicted Z-score. The independent variable is board diversity. The solid line represents estimation using quantile regression techniques and the shadowed area the corresponding 95 percent confidence interval for the quantile regression estimation. The maximum point: Board diversity, 2.50 and Z-score, 0.15.

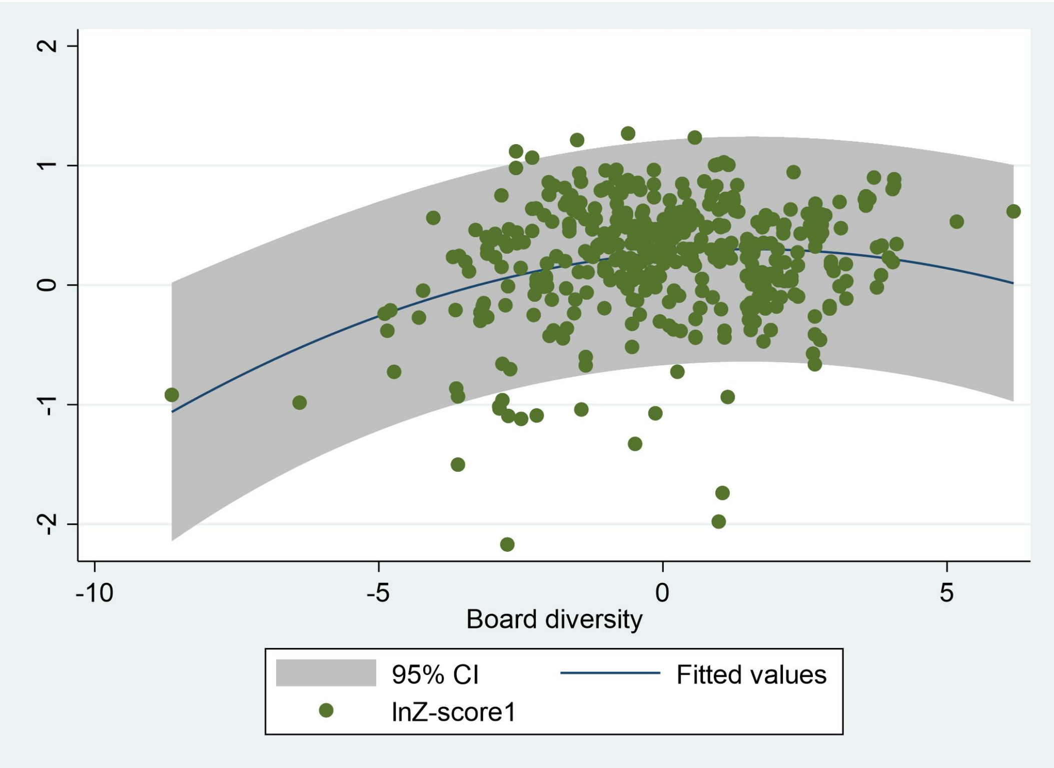


Figure 3.2. Graphical display of bank risk (predicted Z-score) across spectrum of percentage of female.

The dependent variable is predicted Z-score. The independent variable is percentage of female. The solid line represents estimation using quantile regression techniques and the shadowed area the corresponding 95 percent confidence interval for the quantile regression estimation. The maximum point: Pct_Female, 0.20 and Z-score, 0.20.

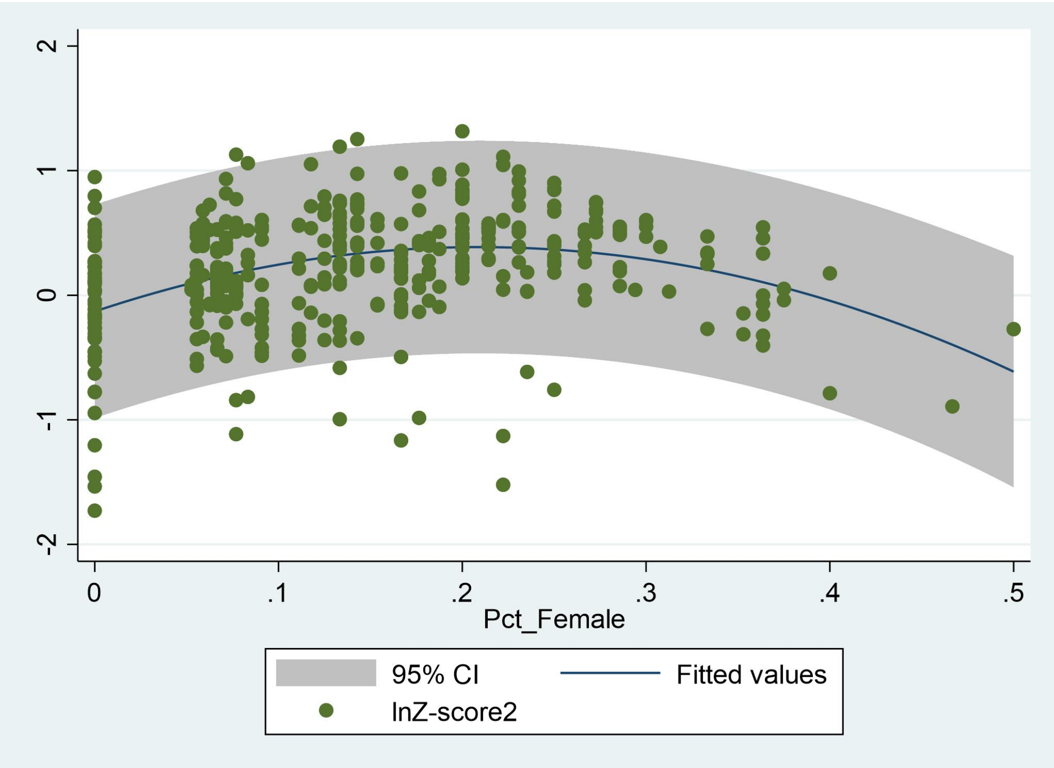


Figure 3.3. Graphical display of bank risk (predicted Z-score) across spectrum of standard deviation of age.

The dependent variable is predicted Z-score. The independent variable is standard deviation of age. The solid line represents estimation using quantile regression techniques and the shadowed area the corresponding 95 percent confidence interval for the quantile regression estimation. The maximum point: Std_Age, 9.00 and Z-score, 0.10.

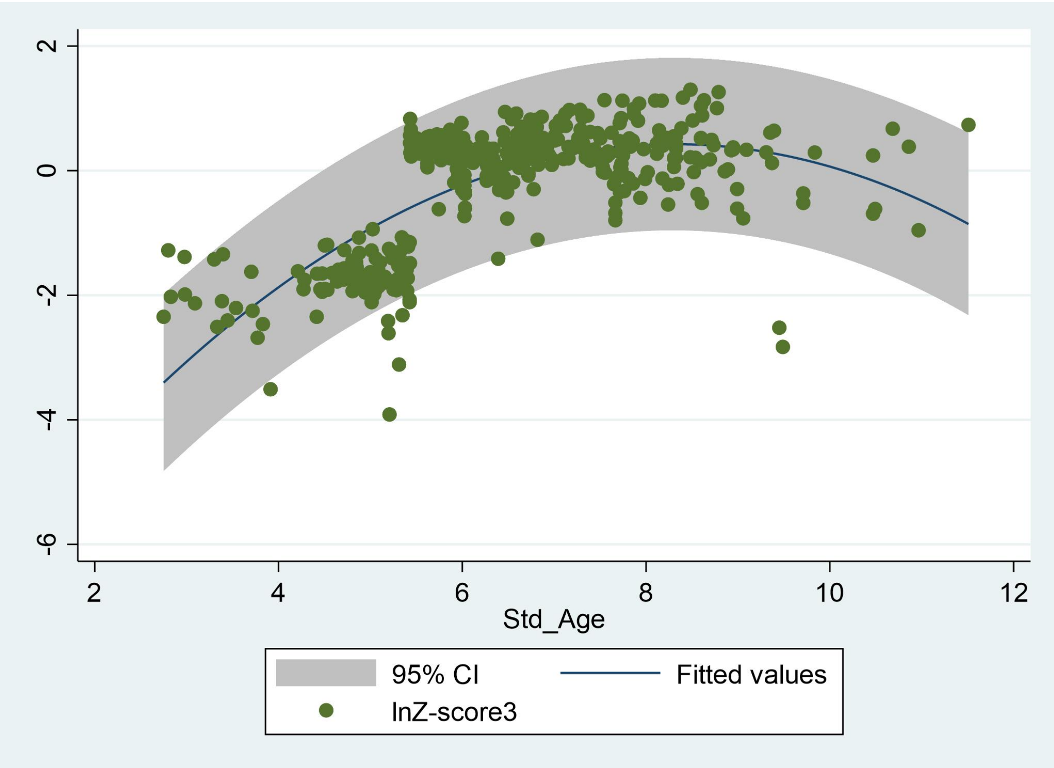


Figure 3.4. Graphical display of bank risk (predicted Z-score) across spectrum of education background.

The dependent variable is predicted Z-score. The independent variable is education background. The solid line represents estimation using quantile regression techniques and the shadowed area the corresponding 95 percent confidence interval for the quantile regression estimation. The minimum point: 1-HHI_Education, 0.65 and Z-score, 0.10.

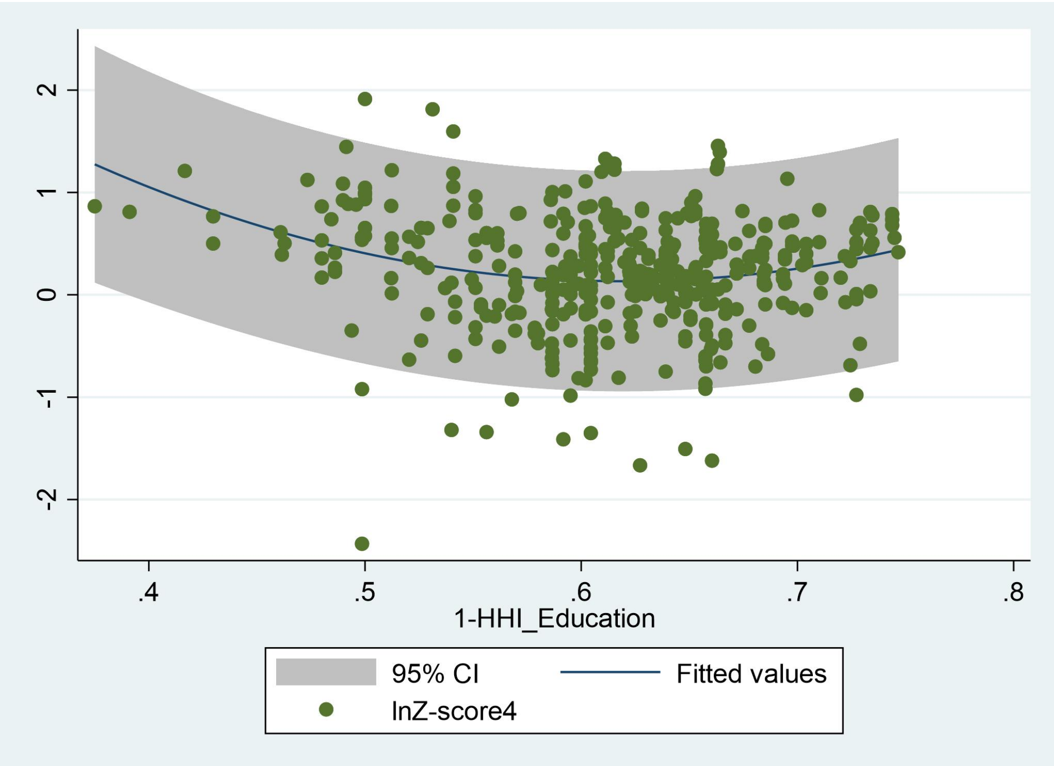
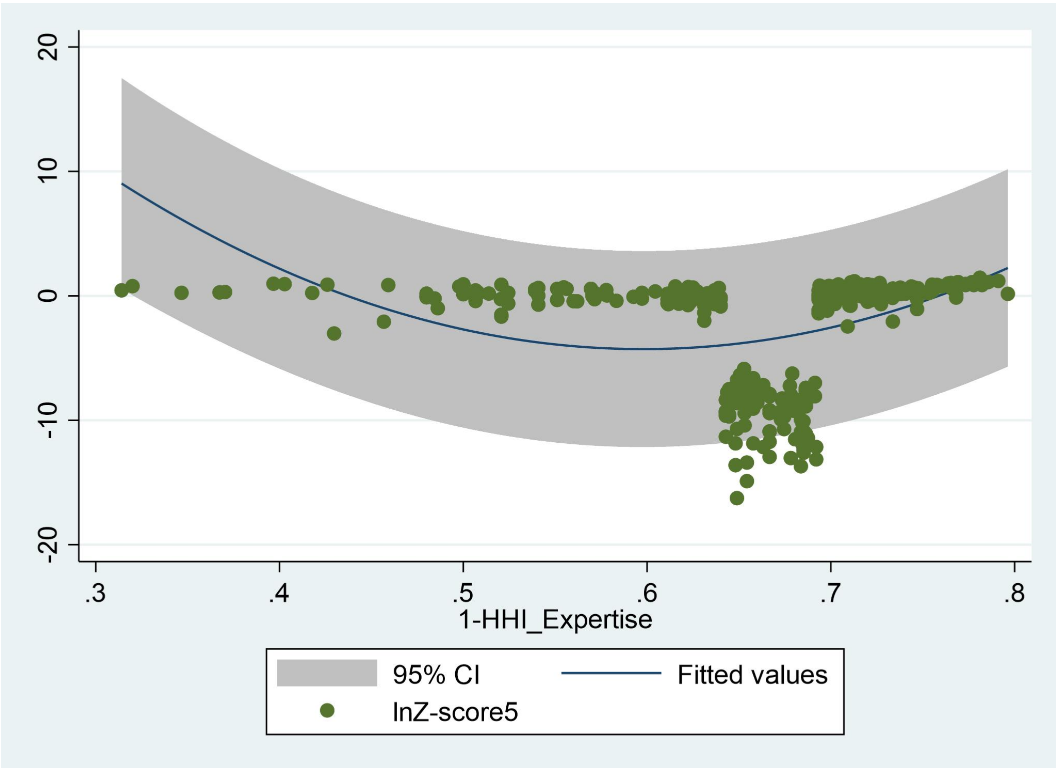


Figure 3.5. Graphical display of bank risk (predicted Z-score) across spectrum of financial expertise.

The dependent variable is predicted Z-score. The independent variable is financial expertise. The solid line represents estimation using quantile regression techniques and the shadowed area the corresponding 95 percent confidence interval for the quantile regression estimation. The minimum point: 1-HHI_Expertise, 0.65 and Z-score, -2.00.



CHAPTER 4

Technology and bank risk

Abstract: This paper contributes to the investigation into the relationship between technology and bank risk, using the samples of Chinese commercial banks from 2007 to 2020. We measure the technology development ratio using the stochastic frontier model as the main independent variable, and the logarithm of Z-score as the dependent variable. We propose and test an efficiency hypothesis and agency hypothesis. The baseline results are consistent with a dominance of the agency hypothesis where senior managers seek personal rewards that will offset the benefits of technological progress. However, the results of banks with below industry average technological capability as well as banks with top technological capability are consistent with a dominance of the efficiency hypothesis — technological capability improves efficiency in managing risk. Technology development has a negative effect on both state-owned banks and city commercial banks, and the effect on state-owned banks is about 4 times larger than that on city commercial banks. In robustness tests, we further find banks' past risk level can facilitate better risk management. At the same time, the banks' past level of technology will continue to facilitate its technological innovation and risk assessment. Moreover, external FinTech is an important factor that will to some extent exacerbate bank risk. On one hand, when FinTech cooperates with banks in the absence of sufficient regulation, it increases bank risk exposure but, on the other, it divides part of the bank's business.

JEL Classification: G21; G28; L25

Keywords: Risk; Technology; Commercial banks; China

4.1. Introduction

In recent years, there have been constant references to technological innovation in banking, notably FinTech. The main impact of technological innovation in the banking industry has been through upgrading new products, services and processes. It is said that more advanced technological capability not only increases work efficiency and improves service and product quality, but also breaks down regional barriers and achieves more direct communication with customers. Lee et al. (2021) state that Fintech innovations help banks improve cost efficiency and enhance the technology used by banks. Berger (2003) notes that banks are strongly influenced by technologies, especially those using financial technologies to create and value new securities, estimate return distributions and make portfolio decisions as this significantly increases overall productivity. By increasing spending on information technology, banks enhance productivity and thus become more competitive (Swierczek, Shrestha, 2003). Banks have improved their risk management capabilities and risk tolerance with the help of technology; however cooperation with FinTech companies bring unknown potential risks, including technical, operational and geopolitical risks (Cheng, Qu, 2020; Li et al., 2022). Over 400 commercial banks all over the world invested in FinTech with $210 billion in 2021, serving small and medium-sized business to transform to compete (KPMG, 2022). In 2020, China's listed banks in A-share invested about $30 billion in information technology, up 25% year-on-year, accounting for 10.7% of the banking industry's net profit of $272.23 billion that year. And large commercial banks generally invest 2.70%-3.15% of their revenue in FinTech, with several banks investing more than $15 billion in technology (Sina Finance Research Institute, 2022). China Banking Industry Digital Transformation Research Report (2022) introduces that the main direction of investment of banks in technology resources is to use technologies such as big data, artificial intelligence, cloud computing, blockchain, 5G and IoT to reconfigure the existing architecture, which promotes the in-depth application of financial technology in financial infrastructure, digital currency, private banking and wealth management, supply chain finance, green finance and inclusive finance, etc.. According to Mobile Payments App Revenue and Usage Statistics (Curry, 2023), there are about 2.1 billion mobile payment app users in the world, and mobile payments transaction volume reached $1.7 trillion in 2021. China has by far the highest mobile payment adoption rate at 87.3%, followed by South Korea and the United States, with 45.6% and 43.2%, respectively. Germany and France have much lower adoption rate, with 19% and 21.1%, respectively, partly because banks and customers are hesitant about mobile payments. By the end of 2021, the scale of China's online payment users reached 904 million, an increase of 49.29 million from the end of 2020. In particular, about half of Internet users are used to managing liquid deposit for financial investment and daily consumption through the use of Alipay and WeChat (the China Payment Clearing Association, 2022; iRearch, 2022).

Based on the background of technological innovation and application, this study investigates the relationship between technology and bank risk. In spite of the close connection between technological innovation and bank risk, most existing studies examine it from a qualitative perspective or through a quantitative analysis of FinTech and fail to explore other quantitative approaches. Most literature focuses on how FinTech affects bank efficiency and performance (Lee, et al., 2021; Fuster et al., 2019; Zhang et al., 2019). The overriding focus on FinTech is an evident limitation of technology and bank risk literature (Buchak et al., 2018; Boot et al., 2021; Li et al., 2022). One of the difficulties that arises is that technological innovation is hard to quantify and there is no uniform calculation of the FinTech index, which may therefore yield opposite conclusions. To avoid this inconsistent calculation, we use the bank's financial data and calculate the technology development ratio (TDR) as our technology variable. In this context, we propose two competing hypotheses to determine the impact of technology on bank risk. Firstly, the efficiency hypothesis whereby technological progress increases scale economies over time and allows banks to better manage their risks. Secondly, the agency hypothesis whereby banks conduct annual staff appraisals, and senior managers with excellent appraisal results are motivated through performance incentives.

To test these hypotheses, we collect 1181 observations from 134 Chinese commercial banks over the 2007-2020 period as our dataset to investigate the impact of technology on bank risk. These banks include state-owned commercial banks, joint-stock commercial banks and city commercial banks. We exclude rural commercial banks from our samples as data is frequently unavailable.

We test the hypotheses by regressing the bank risk on TDR. The empirical results are consistent with these two hypotheses: under the efficiency hypothesis, Chinese commercial banks with less technological capability devote more attention to risk management, while banks with top technological capability have complete control of the business and assets and therefore manage risks efficiently. Under the agency hypothesis, advanced technological capability allows managers to adopt an aggressive strategy that leads to higher risks.

Our analysis also shows some additional findings. In robustness tests, we consider three possible endogenous situations: the risk in the previous period, TDR in the previous period and the external FinTech factor constructed by the Institute of Digital Finance Peking University (2021). We find that past bank risks will result in lower bank risk in the current period because banks improve their risk control capabilities through continuous risk assessment. Simultaneously, banks' previous technological capability will also encourage them to keep up with technological innovation. Finally, external technological factors will cause bank risk to rise to some extent due to the irregularities and lack of supervision of the cooperation with third-party FinTech companies.

Our study makes two novel contributions to the literature. First, the extant literature's use of quantitative empirical research limits the examination of technology's impact on bank risk. Most studies that discuss the impact of technology on banks in China use a FinTech index. For example, Lee, et al. (2021) construct a FinTech development index by using the data of the total number of FinTech companies, the total registered capital, the total number of financing events, and the total amount of financing from Fintech Beta to represent the degree of FinTech development. Cheng and Qu (2020) use a similar methodology to construct different FinTech indices, while Pérez-Martíet et al. (2018) use big data, and Zhao et al. (2022) use the FinTech development index. Li et al. (2022) use web crawler technology to construct an internal bank-level FinTech index. However, calculations of FinTech indices and data acquisition sources are not uniform and suffer from human processing bias. The first novelty of this paper is that we use banks' financial data to calculate the technology development ratio as the main technology factor by using a stochastic frontier model following by Lee, Huang (2018) and Casu et al.(2016). This method takes fixed financial data and has a smaller human processing error than when using the FinTech calculation. We first use a stochastic translog cost frontier function to calculate the total costs of the average banking industry. In the second step, we calculate TDR measured as the distance between the meta-frontier and the bank-specific frontier. In the third step, we employ an OLS model to assess the impact of the technology development on bank risk. The main dependent variable is bank risk measured as the logarithm of Z-score. Secondly, the paper contributes by providing a new management mode for banks and senior managers. Technological progress leads to more efficient bank operations and lower operating costs, while causing senior managers to pursue their own interests, which creates an agency problem. Therefore, to avoid this problem, banks need to take senior management rewards into account and set reasonable performance targets and performance rewards. At the same time, they need to strengthen their internal monitoring mechanism and regularly report the risk level of assets to reduce the possibility of forming non-performing assets.

The remainder of the paper is organized as follows. Section 2 presents the literature review and hypotheses, and Section 3 describes methodology. This is followed by the data in Section 4 and the empirical results in Section 5. Section 6 sets out the robustness tests and Section 7 concludes.

4.2. Literature review

Previous research use two alternative methods to define technological factor: constructing a technology index or measuring the technology development using a meta-frontier function. For instance, Lee, et al. (2021) construct a FinTech development index by using the data of the total number of FinTech companies, the total registered capital, the total number of financing events, and the total amount of financing from Fintech Beta to represent the degree of FinTech development. Li et al. (2022) construct a FinTech innovation index by collecting the number of news articles related to the FinTech innovation of each bank in the Baidu News and normalizing this. Chen and Qu (2020) adopt a similar method by using web crawler technology and word frequency analysis to measure the FinTech index. Zhao et al. (2022) use patent data and construct a FinTech development index to define the technology factor. In the alternate method, Hayami and Ruttan (1971) first introduce a meta-production function, and any change in production coefficients is regarded as technical change. Battese and Rao (2002) propose that a stochastic meta-frontier function can be used to investigate the technical efficiencies of firms in different groups. Similarly, Lee and Huang (2018) calculate technology gap ratio (TGR) to represent advanced technology. Casu et al. (2016) use a parametric meta-frontier Divisia index to identify technology developments. Detecting a technology development involves two steps: first, setting the meta-frontier; second, calculating the technology development.

Teece (1986, 2006, 2018) was the first to propose a comprehensive theory to explain the factors that impact the division of profit from innovation (PFI). In the intervening decade, the business environment has changed further. The Internet has evolved from being a simple searching tool to being accessed interactively anytime and anywhere. The means of communication has evolved, from phone and email toward messaging apps that also serve as portals for shopping and a host of other services. Breakthroughs and developments in blockchain, artificial intelligence and 5G wireless communications have also an impact on business and society. PFI framework identifies the contingencies for profiting from innovation in different settings. Under PFI framework, this study will focus on general purpose technologies (GPTs), including enabling technologies and complementary assets. GPTs have three characteristics: (1) they are in wide use; (2) they are capable of ongoing technical improvement; (3) they enable complementary innovations in application sectors. Enabling technology is more internal technology for banks that is widely used, such as Internet, office software, other applications and communication technologies. Banks use such technology primarily to improve their efficiency, reduce costs, improve risk management capabilities and reduce risk-taking.

In empirical analysis, Berger et al. (2007) propose and test an efficiency and a hubris hypothesis; they find the efficiency hypothesis prevails over the hubris hypothesis, indicating that large, multimarket banks compete more effectively against small, single-market banks as a result of technological progress. In another paper by Berger et al. (2003), they analysis the effect of internet banking, electronic payments technologies and information changes on bank performance, and confirm that banks benefit from technological improvements in costs and lending capacity. Li et al. (2022) use panel data of 65 commercial banks between 2008 and 2020 and find that a bank with a higher level of FinTech innovation takes fewer risks. Moreover, efficiency due to technological progress allows banks to reduce cost (Margono et al., 2010). Lee and Huang (2018) find the similar results, using dataset cover 114 Chinese commercial banks to estimate cost efficiencies for banks operating under different technologies for the period 2003-2014.

Complements are pervasive throughout the economic system, and particularly in technology development and business transformation. The notion of complementarity is that the marginal value of a variable increases with another variable. In this paper, complementarity is more related to external technology, for example, the emergence of Alipay and WeChat, which enable consumers to use mobile payments. However, it is important to note that such external technologies are not simply complementary, as it also contains competitive. On one hand, FinTech innovation forces banks to improve their own technological innovation through competition; on the other, it leads to cooperation among banks to attract more customers through their own platforms and channels.

Empirical results also show different results. Some argue that Fintech has a positive impact on banks. Cheng and Qu (2020) use a similar methodology to Li et al. (2022), they find that FinTech significantly reduces banks' credit risk, and notably that this effect is weak among large, state-owned and listed banks. Pérez-Martíet et al. (2018) use big data to predict borrower behavior and thus help reduce risk. Lee et al. (2021) use the dataset covers 12846 samples from 2003 to 2008 to estimate effect of technological innovation on bank efficiency. The findings of Lee et al. (2021) suggest that FinTech development has a significant impact on banks. It improves both cost efficiency and technological capacity, which in turn boosts the risk control capacity.

Other arguments support the opposite opinion. For instance, Zhao et al. (2022) find FinTech innovation harms banks' profitability and asset quality, which increases bank risk. Buchak et al. (2018) argue that the shadow bank market share in the residential mortgage business increased sharply in United States due to technological innovation, to the detriment of the performance of traditional banks.

Based on PFI framework and literature, we propose two competing hypotheses. The first is the efficiency hypothesis following Berger et al. (2007) whereby technological progress increases scale economies over time and allows banks to better manage their risks. Improvements in GPTs enable senior management to oversee multiple operations simultaneously, while advances in applied finance enable banks to manage the risk of larger portfolios more effectively. Similarly, improved technology allows banks to operate more efficiently across different branches over larger geographic areas, reducing the cost of monitoring and communicating with employees, as well as providing high quality services to clients.

Secondly, we propose the agency hypothesis whereby banks conduct annual staff appraisals, and senior managers with excellent appraisals are motivated through performance incentives, such as large bonuses. These senior managers will try relatively aggressive business strategies to obtain higher rewards, often at the expense of bank performance and accompanied by higher risks. At the same time, PFI framework notes that technological innovation is often accompanied by uncertainty and instability, making it difficult for inventors to benefit from the technology at the outset (Teece, 1986, 2006, 2018). Therefore, under this hypothesis, the potential risks associated with the pursuit of personal rewards by senior management offset the benefits of technological advances.

If the efficiency hypothesis dominates empirically, the impact of technology on bank risk should be positive as improvement in technology helps banks to manage risk more efficiently. On the other hand, if the agency hypothesis dominates empirically, the results are the inverse as the steady development of technology enables senior managers to adopt aggressive strategies in pursuit of larger rewards that result in higher risks.

4.3. Methodology

4.3.1. Meta-frontier model and technology gap

Previous studies have employed different approaches to measure technological development in the banking sector, including the construction of a technology index or the utilization of a meta-frontier function. However, the use of technology indices has yielded inconsistent results due to variations in data sources and construction methodologies. To address this issue, this study primarily adopts the meta-frontier model to construct a technology development factor using bank financial data. The advantage of using the meta-frontier measures lies in their ability to statistically eliminate certain factors that may introduce errors, such as data-collection errors and calculation errors associated with index construction. Consequently, the impact of technology development factors on bank risk, as determined through statistical methods, is more consistent and plausible compared to the results obtained from different approaches used to construct technology indices.

The first step is to set meta-frontier. Followed by the previous studies (Pyatt and Shephard,1972; Casu, Ferrari and Zhao 2013; Casu et al. 2016), the stochastic frontier model was normally adopted a cost, production or profit function with a composite error term. In this paper, we use a stochastic translog cost frontier as follows:

$$\begin{aligned}
\mathrm{lnC}_{it} &= \alpha_0 + \sum_{m=1}^{2} \alpha_m lny_{mit} + \sum_{j=1}^{2} \beta_j lnw_{jit} + \sum_{m=1}^{2}\sum_{q=1}^{2} \alpha_{mq} lny_{mit} lny_{qit} \\
&+ \sum_{n=1}^{2}\sum_{j=1}^{2} \beta_{nj} lnw_{nit} lnw_{jit} + \sum_{j=1}^{2}\sum_{m=1}^{2} \gamma_{jq} lnw_{jit} lny_{mit} + \lambda_1 t + \lambda_2 t^2 + \sum_{m=1}^{2} \theta_m t lny_{mit} \\
&+ \sum_{j=1}^{2} \delta_j t lnw_{jit} + \sum_{p}^{p} \eta_p E_{it} + \nu_{it} \\
&+ \mu_{it} \qquad (4.1)
\end{aligned}$$

where C_{it} is the total cost of bank i at time t. We use inputs and outputs variables following Sealey and Lindley (1977) and Casu et al. (2016). y are total loans (y_1) and other earning assets (y_2). w are interest expenses over customer and short-term funding (w_1) and non-interest expenses over total assets (w_2). t is time, t=1 indicates the first year the financial data of bank i is available. We also use the interaction of inputs, outputs and year to capture neutral and non-neutral technical change and technological progress. E denotes control variables. In this case we consider the size (log of asset), risk (capital to assets ratio), diversity (1- the difference between net loans and other earning assets over total earning assets) and macroeconomic factor (GDP for each province where the bank headquartered). ν_{it} denotes components of noise ν_{it} ~N$(0, \sigma^2)$ and μ_{it} denotes inefficiency.

The basic meta-frontier assumption is that each bank is able to reach the k different technologies which belong to a common meta-technology set. In other words, the meta-frontier allows for the possibility of technological spillovers between banks. Following Battese and Rao (2002), Casu et al. (2016) and Lee and Huang (2018), the technology development ratio (TDR) was measured as the distance between the meta-frontier and the bank-specific frontier. If the bank-specific frontiers are given as follows:

$$\mathrm{C}_{it}^{k} = f\left(X_{it}\beta^{k}\right)\exp\left(\upsilon_{it}^{k} + \mu_{it}^{k}\right) = \exp\left(X_{it}\beta^{k}\right)\exp\left(\upsilon_{it}^{k} + \mu_{it}^{k}\right) \tag{4.2}$$

with bank-specific parameters β^{k}.

The meta-frontier envelops the k estimation and it uses the same functional form as Equation (2), which can be written as follows,

$$\mathrm{C}_{it}^{*} = f(X_{it}\beta^{*})\exp\left(\upsilon_{it}^{*} + \mu_{it}^{*}\right) = \exp\left(X_{it}\beta^{*}\right)\exp\left(\upsilon_{it}^{*} + \mu_{it}^{*}\right) \tag{4.3}$$

$X_{it}\beta^{k}$ and $X_{it}\beta^{*}$ satisfy the inequality $X_{it}\beta^{*} \leq X_{it}\beta^{k}$, because $X_{it}\beta^{*}$ is from the meta-frontier, which shows always the minimum possible cost.

The relationship between Equation (2) and Equation (3) can be rewritten as follows,

$$1 = \frac{\exp\left(X_{it}\beta^{*}\right)}{\exp\left(X_{it}\beta^{k}\right)} \cdot \frac{\exp\left(\upsilon_{it}^{*}\right)}{\exp\left(\upsilon_{it}^{k}\right)} \cdot \frac{\exp\left(\mu_{it}^{*}\right)}{\exp\left(\mu_{it}^{k}\right)} \tag{4.4}$$

where the three ratios of the right-hand side are technology development ratio (TDR), the random error ratio (RER), and the technical efficiency ratio (TER). TDR is the ratio of the predicted variable costs for banking industry divided by each bank's cost under the same conditions. It is assumed that TDR has values from 0 to 1, with a higher value indicating a smaller technology development from the meta-frontier and vice versa (Pyatt and Shephard,1972; Casu, Ferrari and Zhao 2013; Casu et al. 2016).

It should be emphasized that, in other studies, TDR is named as technology gap ratio (TGR) (Casu et al., 2016; Lee and Huang, 2018). We acknowledge that the inputs and outputs for banks are such that meta-frontier cost function models are defined for different groups within the banking industry. However, the meta-frontier does not actually envelop all the banks' observed outputs and inputs, although TDR is bounded (Huang, Huang, Liu, 2014). Another difference in our paper is that we estimate TDR for each bank but not the groups. Therefore, empirically, the estimated individual bank frontiers can be over or under the meta-frontier line. TDR in our case can be over the value 1, which means the bank is more technologically advanced. Hence, we redefine the variable as TDR and use it as the main variable of the technological factor in the next step to estimate the impact of technology on bank risk.

4.3.2 Regression of technology gap on bank risk

After we calculate the TDR, the next step is to estimate the impact of technology factor on bank risk. The baseline model we use is OLS regression as follows:

$$\text{Risk}_{it} = \alpha + \beta TGR_{it} + \delta E_{it} + \mu_{it} \qquad (4.5)$$

We employ the logarithm of *Z-score* as the main variable of bank risk, with larger values indicating lower overall bank risk (Beltratti and Stulz, 2012; Berger, et al., 2015; Boyd and Runkle, 1993; Houston, et al., 2010; Laeven and Levine, 2009; Meslier, et al., 2016). *Z-score* is calculated as the sum of ROA and Capital ratio over the standard deviation of ROA. We also consider the standard deviation of ROA as bank risk in robustness test.

On the right-hand side, TDR is the main independent variable and denotes our technology factor calculated in the previous steps. Under efficiency hypothesis, TDR will have a positive relation to bank risk, whereas under agency hypothesis, it has a negative impact on bank risk.

E denotes the control variables. We consider almost the same control variables as Equation (1), namely the asset size, diversity and GDP across provinces. We control for asset size. Larger banks have a greater capacity to absorb risk than smaller banks (Gulamhussen et al., 2014; Berger, Bouwman, Kick, and Schaeck, 2014). Technological progress improved the performance of large banks relative to small banks (Berger et al., 2007).

We also control for diversification. We use asset diversity which is a measure of diversification across different types of assets (Laeven, L., Levine, R., 2007; Casu et al., 2016). It calculated as 1- the difference between net loans and other earning assets over total earning assets, where other earning assets include securities and investments. It is important to control for this standard indicator of diversification in banking research, as the more diversified banks tend to require more advanced technology. In addition, previous studies shows evidence that diversification tends to have a positive or negative impact on bank risk (Laeven, L., Levine, R., 2007; Laeven, Levine, 2009; Shim, 2013; Yang et al., 2020; Schmid and Walter, 2009).

To control for macroeconomic activity, we account for GDP per provinces by using the natural log for this variable. A higher level of GDP is positively correlated with the quality of technological infrastructure within a province, which in turn contributes to the advancement of technology within banks. Additionally, a bank headquartered in the province with higher level of GDP has usually a well-developed corporate governance system and a robust risk control capability.

We also add ownership by state or state-owned corporations given that to some extent a bank with more state owned shares has a higher risk-taking level. Finally, we control for the fixed effect to control bank specific effects. The fixed effect accounts for average differences across banks that are not captured by the other exogenous variables. In order to accurately measure the impact of a bank's technology level on bank risk, it is important to control for bank fixed effects. This is because the technological level of a bank can be influenced by various factors related to the local economy, population size, population education, and local policies, even when controlling for the level of GDP in each province. By including bank fixed effects in the analysis, we can isolate the specific impact of the bank's technology level on bank risk, while accounting for any potential confounding factors associated with the bank's location. Table 4.1 summarizes all the variables and definitions.

[Inserting in Table 4.1]

4.4. Data

The sample used in this paper comprises 134 Chinese commercial banks according to the List of Banking Financial Institution Legal Persons (China Banking and Insurance Regulatory Commission, 2021) over the 2007-2020 period. We exclude 13 city commercial banks and rural commercial banks because of unavailable annual reports and financial data. The data is collected from annual reports from each bank's website and Sina Finance. Following Meslier, et al. (2016), we calculate return on asset (ROA) and return on equity (ROE) by using the rolling window of 3 years. As the first available ROA and ROE is from 2009, we exclude 2007 and 2008 from our regression analysis. We further screen our dataset and exclude the samples without the following data: total cost, total loans, net loans, total asset, other earning assets, interest expenses, deposit, short-term funding, operating costs and other expenses. The final sample comprises 1181 observations, including 6 state-owned banks, 12 joint-stock commercial banks and 114 city commercial banks. Table 4.2 presents summary statistics for our variables.

In terms of risk, commercial banks have a mean ln(Z-score) and Stvd ROA of 4.41 and 0.14 respectively, the minimum value and maximum value of ln(Z-score) are 1.46 and 9.20 respectively, indicating that the commercial banks in China have different risk levels, and most commercial banks are less likely to default. The range of TDR goes from 0.43 to 2.19; the point under and over the meta-frontier line means that a bank has less and more technological capability respectively. In relation to control variables, the average log of total asset is 26.26 and the capital to asset ratio is 7.13. The assets of Chinese commercial banks are more diverse, with the average value of 0.71. The average GDP per capita at the provincial level is over $5600.

[Inserting in Table 4.2]

[Inserting in Table 4.3]

Table 4.3 shows descriptive statistics for different ownership categories by years. The results show interesting differences. TDR clearly suggest that with regard to different bank types, state-owned banks have the most advanced technological capacities, followed by joint-stock banks and city commercial banks. Similarly, state-owned banks has lowest bank risk, with ln(Z-score) of 2.93, higher than joint-stock commercial banks (2.23) and city commercial banks (2.15). The total annual cost index of state-owned banks is around 26.71, slightly higher than that of joint-stock banks at 25.05 and city commercial banks at 22.38. Moreover, state-owned banks have much larger total loans (y1) and other earning assets (y2) than other banks. However, other earning assets (y2) and diversity have seen a relatively large decline in 2018, mainly due to the trade war between the US and China in 2018, which has a negative impact on the Chinese economy and led to a decrease in other earning assets and diversity. FinTech index suggests that China's FinTech level has been gradually developing. Nowadays, FinTech has been integrated into people's work and life, for example, the QR code down payment that can be seen everywhere. The level of FinTech development is about 7 times higher than ten years ago.

4.5. Empirical results

Table 4.4 shows descriptive statistics for the impact of technology on bank risk. Models 1 and 2 are baseline regression results without and with the fixed effect respectively. The coefficient of TDR in Model 1 is insignificant, while that of Model 2 with the fixed effect is negatively significant at the 1% level. The results are consistent in Models 3 and 4; the coefficient of TDR in Model 3 is insignificant but that of Model 4 is negatively significant at the 1% level after adding the fixed effect. Both results indicate that a bank with more technological capability has increased risk. However, these results are inconsistent with Li et al. (2022). However, whereas these authors consider only 65 commercial banks, with 6 state-owned commercial banks, 10 joint-stock commercial banks, 29 city commercial banks, 17 rural commercial banks, and 3 village banks, our sample includes 134 commercial banks and is therefore more comprehensive. Moreover, we adopt technology development as our main independent variable which is different from that of Li et al.(2022).

The negative impact of TDR is in line with the dominance of the agency hypothesis — senior managers pursue higher personal rewards and are more likely to adopt an aggressive business strategy, which therefore results in higher risk for banks. At the same time, as banks continue to innovate in technology, such as office systems, customer management systems, and other software, it greatly increases the efficiency of bank managers, which makes bank managers more willing to pursue higher risk-taking.

In terms of control variables, *lnSize* has a significant but different effect in Models 3 and 4, while *Diversity* is negatively significant in both these models, thus indicating that banks with more diversified business have increased bank risk. This may be explained by the fact that the more diversified the bank's business is, the more difficult it is to control and manage risk. Ownership proves insignificant in all the models. Clients generally believe that almost all Chinese commercial banks belong to state-owned enterprises or local governments even though the ownership structure of some commercial banks contains few governmental shareholders. In addition, the share or equity holdings of top management in the Chinese banking industry are very small, while the well-established internal and external supervisory and management mechanisms of banks effectively avoid conflicts between the personal and collective interests of senior management. As a result, the ownership and interests of top management have little influence on daily operations and bank performance. *lnGDP* has a statistically significant and positive effect on bank risk, which indicates a greater demand for financing in cities with a larger GDP; the likelihood of default in this financing is smaller because these customers are wealthier than those in cities with a lower GDP and the corresponding default risk is also smaller.

[Inserting in Table 4.4]

We further divided the sample into four groups based on quartiles to determine the inflection point where the efficiency hypothesis dominates. The results are reported in Table 4.5. We observe that the coefficients of TDR of the first, second (TDR<1), and fourth quartiles (TDR>1.045) are positive in the models with and without the fixed effect, while the TDR coefficients in the third quartile (1<TDR<1.045) become negative. This indicates that banks with below-industry-average technological capabilities and banks with top technological capabilities are dominated by the efficiency hypothesis, while those with above-industry-average but not top technological capabilities are dominated by the agency hypothesis. The reason behind this is that banks with low technological capabilities (located in the first and second quartile) are more risk averse and therefore will use technology for risk management and risk prevention more than for other areas such as cost reduction. Banks with top technology capabilities can use technology to their advantage to cover a broader range of assets and operations, and also manage risk more efficiently. In contrast, banks in the upper quartile, where technology capabilities are above the industry average but not at the top, focus more on performance and development. Managers in such banks prefer to adopt aggressive business strategies for personal rewards. However, the current technological capabilities are not yet at the level required for manager's the aggressive business strategies and therefore agency hypothesis dominates, exposing the bank to higher risk.

[Inserting in Table 4.5]

According to ownership structure, we divide the samples into state-owned banks, joint-stock banks and city commercial banks. Table 4.6 shows the impact of technology on bank risk by bank types. The effect of TDR is only significant on state-owned banks and city commercial banks. The TDR of -3.444 in Model 2 and -0.868 in Model 6 suggests that state-owned banks and commercial banks have higher risk with the technology development, but the effect of TDR on state-owned banks is about 4 times larger than that on city commercial banks. The likely reason is that state-owned banks have the nature of being "Too Big To Fail". It is the cornerstone of China's banking industry, and therefore it has a higher risk-taking capacity. On one hand, innovations in technology are often first to be applied in state-owned banks. After showing that the risk is manageable, it is then extended to other commercial banks. On the other hand, bank managers of state-owned banks usually have higher education, more specialized knowledge and skills than those of joint-stock banks and city commercial banks. They are more likely to adopt more aggressive business strategies in their business activities, which therefore results in higher risk for banks.

[Inserting in Table 4.6]

4.6. Robustness tests

4.6.1. Alternative measures of risk

In this section, we examine whether the results of the alternative measures of bank risk are consistent with the baseline model. We replace Stdv.ROA as the dependent variable. Models 2 and 4 include the fixed effect. The results are reported in Table 4.7.

[Inserting in Table 4.7]

The coefficient of TDR in Models2 and 4 is positive and significant, which is inconsistent with the baseline results. In addition, we use equity to asset ratio as the dependent variable. The results are shown in Models 5 to 8. The coefficients of TDR are all negative, which is consistent with the baseline results. We assume that exogenous variables may have influenced TDR; this will be tested in Chapter 4.6.4.

4.6.2. Alternative measures of technology

To verify the feasibility of our independent variables, we will employ technological progress as the independent variable that is often used in the existing literature (Baltagi, Griffin, 1988; Margono et al., 2010; Oh et al., 2012). The estimation of technological progress (TP) is defined as the derivative of output or cost function with respect to time. In our analysis, we use cost function in Equation (1), therefore we derive the cost function with respect to time, TP is estimated as follows:

$$\mathrm{TP}_{it} = \lambda_1 + 2\lambda_2 t + \sum_{m=1}^{2} \theta_m lny_{mit} + \sum_{j=1}^{2} \delta_j lnw_{jit} \tag{4.6}$$

After we calculate the TP, we insert TP into baseline regression, the results are reported in Table 4.8.

[Inserting in Table 4.8]

The empirical results are consistent with previous results — TP is negatively significant to bank risk in Model 1 to Model 4, which indicates that agency hypothesis dominate to the efficiency hypothesis. The risks associated with aggressive business strategies and the pursuit of larger portfolios by management for personal gain offset the advantages of technological advances and technological innovation.

4.6.3. Interaction variable

In order to determine the relationship between asset size and bank risk, we add an interaction variable, TDR*lnAsset. We believe that the larger the size of bank assets, the more advanced the technology needed by the bank to manage them. At the same time, the more advanced technology a bank owns, the easier it will be for the bank to develop business and increase its assets. The results are shown in Table 4.9. The coefficients of TDR become positively significant, while those of the interaction variable TDR*lnSize are negatively significant at 1% and 5% respectively. The findings indicate that a bank with more advanced technological capability has fewer risks, while a large bank with more technological capability has more risks. This is consistent with the results in Table 4.4, namely efficiency hypothesis prevails for large banks as they usually own advanced technological capabilities; in other words, better technology helps banks manage risk more efficiently. At the same time, unlike small-sized banks, most large-sized banks are state-owned and have the attribute of "Too Big To Fail"; these banks usually have top technological capabilities to manage and control risk.

[Inserting in Table 4.9]

4.6.4. Endogeneity and instrumental variables

This section addresses the potential endogeneity of the technology variable. Following Li et al. (2022), we consider three different situations that may affect bank risk. First, a one-period lagged explanatory variable, L.Risk; as bank risk may persist over time, bank risk may be influenced by the previous period. In this case, we use the GMM model, which is one of the most appropriate models for dynamic panel data. As shown in Table 4.10, L.Risk has a positively significant effect in all the models, which indicates that previous risks serve as a warning for current risks. TDR is still negatively significant in Models 1, 4, 5 and 6, which is consistent with our baseline results — agency hypothesis dominates.

Second, the current level of technological development of the bank also depends on the technological level in the previous year. Hence, we consider the previous year's TDR as an instrument variable (TDR_{t-1}). We use the two-stage least squares (2SLS) model. As can be seen in Table 4.11, in the first stage in Model 1, TDR_{t-1} is statistically significant. In the second stage of 2SLS in Models 2 to 4, the coefficients of TDR are statistically significant. The technological innovation of banks is in line with their social progress and development. The previous level of technology is the foundation for the bank's future technological innovation. The bank has revised and updated its previous technology to make it more efficient in managing risks, reducing staff costs in communication and business across departments and regions, and developing higher quality services. Under the endogeneity of previous TDR, efficiency hypothesis dominates over agency hypothesis. The Wu-Hausman tests are all rejected at 1%, indicating that TDR_{t-1} is not exogenous.

Third, we consider the external technology factor - FinTech as an instrument variable. FinTech innovation can affect bank risk. On one hand, FinTech companies capture the market share of banks such as in the lending business but, on the other, they collaborate with banks to expand business such as selling funds (Lee et al., 2021; Li et al., 2022). We employ the FinTech data constructed by the Institute of Digital Finance Peking University (2021), which presents a wide coverage of business activities such as payments, deposits, loans, insurance, credit services and securities across provinces. By weighting the overall index of each province, we calculate a comprehensive index for China as a whole in that year. Again, we use the two-stage least squares (2SLS) model. As shown in Table 4.12, Wu-Hausman tests in Models 2 3, 6 and 7 show that FinTech is a valid instrument variable. However, TDR is only negatively significant in Models 3 and 7, which indicates that external technology factor affects bank technology innovation to some extent, especially in large-sized banks, and thus increases their risks. These results are explained largely by the rapid development of third-party FinTech companies in China in recent years. Under the agency hypothesis, managers adopt aggressive strategies to start cooperating with FinTech companies such as Alipay and WeChat in order to reach their business goals. While some clients use these apps to buy bank investment products, others users use them to borrow short-term loans. However, China lacks monitoring and regulation of these new FinTech companies and their growth may cause them to stray to the edge of the law for profit, creating uncontrollable systemic risks. For example, P2P thunderstorms were frequent from 2018 to 2020. P2P platforms failed to repay investors' principal and interest because of payment delays or business problems, resulting in platform shutdowns, liquidations, insolvency and collapses. Therefore, the process of cooperation with third-party FinTech companies has to some extent increased banks' risks.

[Inserting in Table 4.10]
[Inserting in Table 4.11]
[Inserting in Table 4.12]

4.7. Conclusion

This paper examines the effect of technology on bank risk. We propose two hypotheses. Under efficiency hypothesis, technological progress helps banks improve working efficiency and manage risks; on the other hand, under agency hypothesis, senior management's pursuit of personal gain could offset the benefits of technological advances and lead to increased bank risk. We test these two hypotheses using the panel data of 134 commercial banks; our sample comprises 1181 observations from 2007 to 2020. We adopt the stochastic frontier model to calculate the technology development and use the OLS model to assess the role of this technology factor in bank risk.

Our baseline results are consistent with an empirical dominance of agency hypothesis — the aggressive business behavior of senior management in banks offsets some benefits from technological progress, increasing bank risk. In order to find the inflection point where the efficiency hypothesis dominates, we separate our samples into four groups according to the quartile. The results show that in the first, second and fourth quartile, the efficiency hypothesis dominates over agency hypothesis because banks are more risk averse. It is usually small-sized banks that have less technological capability and they therefore need to pay more attention to risk control; on the other hand, banks with top technological capabilities can use top technology to fully cover a wide range of assets and business. Hence, bank risk is lower both in banks with less technological capability and top technological capabilities . However, when the technological capabilities are at the average level for the banking industry, namely TDR>1, but do not reach top levels, agency hypothesis dominates over efficiency hypothesis. These banks have enough technological capabilities to control risk and will pay more attention to assets and business expansion. The risks posed by management's aggressive strategy outweigh the advantages offered by technological advances and will therefore increase bank risks. We further estimate the impact of TDR on bank risk by different bank types, and we find that the effect of TDR on state-owned banks is about 4 times larger than that on city commercial banks.

Moreover, we obtain additional findings after considering endogeneity. We find that banks will constantly evaluate their own risk profile and optimize their risk control capabilities. Hence, bank risk in the previous period will reduce current bank risk because a bank's technological level in the previous period will encourage the bank to keep updating the current level of technology. Finally, the external technology factor makes banks increase their risks to some extent. A large number of FinTech companies emerged in China from 2015 to 2020. Management enters into partnerships with FinTech companies in pursuit of performance goals and personal gain. However, industry regulation does not match current business development, leading to possible increased risk.

In terms of the research methodology, we use the stochastic frontier model to measure the technology development and estimate the impact of technology on bank risk; this contrasts with existing literature, which uses FinTech as the main explanatory variable to study the impact of technology on bank risk. In terms of implications for practice, our results enable us to put forward the following suggestions. First, we suggest that banks need to continue to improve their technology, as this will not only improve their efficiency, but also reduce their risks and increase their risk-bearing capacity. Second, as banks are encountering new and potential risks when working with third-party FinTech companies, they need to strengthen their internal regulatory and compliance systems and improve their risk management capabilities. Policymakers should note that while the boom in FinTech has energized China's economy, it is also important to prevent FinTech companies from using these technologies to break the law. The government regulator, the China Banking and Insurance Regulatory Commission, needs to establish a sound regulatory system for FinTech, regulate the commercial cooperation behavior between banks and FinTech companies, increase disciplinary measures for violations, and eliminate the systemic risks to banks caused by FinTech companies.

The limitations of this paper are as follows. Due to data availability, rural commercial banks are not considered; this can be addressed in a future study. Regarding risk measurement, only the Z-score and the standard deviation of ROA are considered in this study but other risks, such as credit risk, could be included in future research. Moreover, future studies should examine the impact of the technological level on other aspects of the bank, such as profitability and costs.

Table 4.1: Variable Definitions.

This table provides variable names, definitions, and data sources.

Variables	Definition	Source
Panel A: Meta-frontier		
Dependent variables		
ln(C)	The logarithm of total cost of bank	Annual reports
Independent variables		
y1 (billion USD)	Total loans	Annual reports
y2 (billion USD)	Other earning assets	Annual reports
w1 (%)	Interest expenses over customer and short-term funding	Annual reports
w2 (%)	Non-interest expenses over total assets	Annual reports
t	Time, t=1 indicates the first year the financial data of a bank is available	Calculate
Panel B: Regression		
Dependent variables		
ln(Z-score)	The logarithm of Z-score. Z-score calculated as (ROA+Equity/Asset)/Stdv.ROA. The larger the Z-score, the lower a bank's risk.	Calculate
Independent variables		
TDR	Technology development ratio. The distance between the meta-frontier and the bank-specific frontier	Calculate
Panel C: Control variables		
lnSize	The logarithm of asset.	Annual reports
Capital to asset	Capital to asset ratio	Calculate
Diversity	1- the difference between net loans and other earning assets over total earning assets	Calculate
Ownership	State-owned or state-owned corporation shareholders	Annual reports
lnGDP	The logarithm of the GDP of each province where the bank is headquartered	National Bureau of Statistics
Bank FE	Entity fixed effects.	Bank FE
Panel D: Robustness test		
Stvd. ROA	Standard deviation of return on asset	Calculate; Annual reports
$Risk_{t-1}$	Risk in the previous period	Calculate
TDR*lnSize	Interaction effect between technology development ratio and assets size	Calculate
TDR_{t-1}	Technology development ratio in the previous period	Calculate
FinTech Index	External technology factor, constructed by the Institute of Digital Finance Peking University	Institute of Digital Finance Peking University

Table 4.2: Summary statistics.

This table shows summary statistics for the sample.

Variables	N	Mean	Std.dev.	Min.	Max.	Median
Panel A: Meta-frontier						
Dependent variables						
ln(C)	1181	22.94	1.57	19.73	27.40	22.63
Independent variables						
y1 (billion USD)	1181	110.60	328.79	0.89	2818.18	11.35
y2 (billion USD)	1181	47.58	123.48	0.10	1039.39	8.61
w1 (%)	1181	3.86	10.56	0.92	349.95	3.33
w2 (%)	1181	1.39	0.59	0.02	4.12	1.41
T	1181	5.22	3.14	1	12	5
Panel B: Regression						
Dependent variables						
ln(Z-score)	1181	4.41	0.98	1.46	9.20	4.33
Independent variables						
TDR	1181	1.00	0.09	0.43	2.19	1.00
Panel C: Control variables						
lnSize	1181	26.26	1.63	23.11	31.14	25.90
Capital to asset (%)	1181	7.13	1.78	3.33	32.51	6.95
Diversity	1181	0.71	0.22	0.04	1.00	0.76
Ownership	1181	0.35	0.23	0.00	0.93	0.33
lnGDP	1181	10.22	0.74	7.14	11.62	10.30
Panel D: Robustness test						
Stvd. ROA	1181	0.14	0.14	0.01	1.57	0.10
FinTech Index	1181	5.36	0.52	3.88	5.84	5.45

Table 4.3: Total observations by ownership group.

Total bank observation	Total	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Observation according to ownership	1181	37	50	73	82	95	102	115	118	124	126	132	127
State-owned banks	66	5	5	5	5	5	5	6	6	6	6	6	6
Joint-stock commercial banks	142	12	12	12	12	12	12	12	12	11	11	12	12
City commercial banks	973	20	33	56	65	78	85	97	100	107	109	114	109
Panel A: Dependent variables (mean)													
ln(C)	24.71	23.73	23.92	24.28	24.55	24.65	24.84	24.89	24.86	25.01	25.09	25.01	25.03
State-owned banks	26.71	26.10	26.20	26.49	26.71	26.77	26.92	26.88	26.73	26.80	26.90	26.89	26.91
Joint-stock commercial banks	25.05	23.74	24.02	24.56	24.85	25.06	25.36	25.44	25.44	25.66	25.63	25.47	25.46
City commercial banks	22.38	21.36	21.54	21.78	22.08	22.12	22.28	22.36	22.39	22.58	22.72	22.68	22.73
Independent variables (mean)													
y1(billion USD)	498.21	245.85	292.25	332.91	379.74	427.93	475.72	468.58	531.91	587.47	645.49	706.65	785.30
State-owned banks	1250.42	641.90	762.75	868.10	986.71	1109.43	1227.69	1178.24	1326.86	1435.38	1557.48	1717.41	1898.72
Joint-stock commercial banks	228.14	86.31	104.31	122.02	142.69	163.90	188.06	215.01	254.46	310.76	358.72	379.46	429.74
City commercial banks	16.07	9.33	9.68	8361	9.82	10.45	11.42	12.51	14.40	16.26	20.26	23.08	27.42
y2(billion USD)	186.12	141.74	153.67	158.01	181.47	206.42	223.59	271.09	313.12	329.57	83.57	75.60	99.75
State-owned banks	438.09	383.86	404.69	414.06	454.18	497.47	524.05	616.21	708.02	751.78	141.02	162.33	221.04
Joint-stock commercial banks	107.95	36.38	50.00	54.89	83.46	113.78	137.03	183.63	214.18	217.91	91.10	53.51	67.27
City commercial banks	12.33	4.99	6.31	5.08	6.77	8.00	9.68	13.42	17.15	19.00	18.58	10.97	10.93
w1 (%)	3.16	1.76	1.74	2.85	3.35	3.46	3.79	3.46	3.03	3.59	3.44	3.29	2.98
State-owned banks	2.12	1.67	1.52	2.01	2.46	2.30	2.59	2.35	2.02	2.07	2.12	2.23	2.07
Joint-stock commercial banks	3.70	2.00	2.06	3.74	4.15	4.29	4.85	4.31	3.50	4.02	4.28	3.89	3.37
City commercial banks	3.65	1.62	1.62	2.81	3.43	3.78	3.93	3.72	3.57	4.68	3.94	3.76	3.49
w2 (%)	1.36	1.40	1.40	1.49	1.48	1.50	1.63	1.71	1.42	1.39	1.26	0.93	0.83
State-owned banks	1.29	1.39	1.40	1.48	1.48	1.48	1.57	1.65	1.16	1.18	1.16	0.89	0.83
Joint-stock commercial banks	1.37	1.35	1.38	1.43	1.35	1.43	1.65	1.79	1.70	1.66	1.16	0.79	0.72
City commercial banks	1.40	1.46	1.43	1.56	1.62	1.60	1.68	1.69	1.39	1.32	1.46	1.10	0.94

Panel B: Dependent variables (mean)													
ln(Z-score)	2.26	1.81	1.85	1.86	2.01	2.27	2.32	2.02	2.08	2.14	2.57	2.62	2.26
State-owned banks	2.39	1.88	1.99	1.85	2.06	2.54	2.59	2.12	2.06	2.14	2.79	2.73	2.37
Joint-stock commercial banks	2.23	1.77	1.75	1.86	1.98	2.25	2.16	2.00	2.17	2.20	2.62	2.67	2.25
City commercial banks	2.15	1.78	1.81	1.85	1.98	2.03	2.22	1.95	2.03	2.07	2.30	2.44	2.15
Independent variables (mean)													
TDR	1.00	1.02	1.05	0.99	0.97	0.98	0.95	0.99	1.05	1.06	0.98	0.97	1.00
State-owned banks	1.01	1.03	1.10	1.02	0.95	1.00	0.99	1.01	1.08	1.09	0.97	0.94	0.97
Joint-stock commercial banks	0.99	1.04	1.07	0.96	0.94	0.92	0.88	0.94	1.04	1.07	0.97	0.99	1.04
City commercial banks	1.00	0.98	0.98	1.00	1.00	1.01	0.99	1.00	1.04	1.02	1.01	1.00	0.99
Panel C: Control variables (mean)													
lnSize	12.79	12.50	12.57	12.63	12.69	12.73	12.77	12.79	12.84	12.87	12.90	12.93	12.97
State-owned banks	13.19	12.93	12.99	13.05	13.10	13.14	13.18	13.17	13.23	13.25	13.28	13.31	13.35
Joint-stock commercial banks	12.47	12.00	12.10	12.20	13.30	12.36	12.43	12.50	12.57	12.61	12.63	12.65	12.70
City commercial banks	11.39	11.08	11.14	11.11	11.19	11.22	11.26	11.33	11.41	11.45	11.48	11.51	11.57
Capital to asset (%)	6.79	5.51	5.88	6.25	6.27	6.43	6.86	6.83	6.62	6.97	7.441	7.87	7.93
State-owned banks	6.96	5.33	5.99	6.14	6.59	6.71	7.34	7.02	7.06	7.25	7.49	7.95	8.06
Joint-stock commercial banks	6.13	4.53	5.34	5.66	5.32	5.58	5.76	5.96	5.94	6.58	7.12	7.99	7.96
City commercial banks	7.29	6.69	6.31	6.94	6.90	7.00	7.47	7.53	6.88	7.07	7.64	7.66	7.77
Diversity	0.64	0.66	0.69	0.64	0.68	0.69	0.71	0.77	0.78	0.78	0.45	0.38	0.38
State-owned banks	0.54	0.74	0.69	0.64	0.63	0.62	0.60	0.69	0.72	0.73	0.18	0.17	0.21
Joint-stock commercial banks	0.63	0.63	0.69	0.65	0.71	0.76	0.79	0.80	0.83	0.81	0.35	0.28	0.29
City commercial banks	0.73	0.62	0.71	0.64	0.69	0.70	0.74	0.80	0.79	0.80	0.81	0.69	0.62
lnGDP	4.52	4.23	4.30	4.36	4.39	4.45	4.49	4.51	4.55	4.59	4.63	4.66	4.67
State-owned banks	4.41	4.13	4.19	4.25	4.29	4.33	4.37	4.40	4.45	4.48	4.53	4.55	4.56
Joint-stock commercial banks	4.60	4.33	4.40	4.46	4.49	4.54	4.57	4.61	4.65	4.68	4372	4.76	4.77
City commercial banks	4.54	4.22	4.29	2.35	4.37	4.46	4.50	4.51	4.54	4.58	4.61	4.64	4.66
Panel D: Robustness test													
FinTech Index				48.38	104.53	159.62	182.71	222.32	232.3	274.04	303.07	327.05	344.64

Table 4.4: Impact of technology on bank risk.

This table reports OLS regressions of the relation between the technology development ratio (TDR) and risks over the 2009–2020 period. The dependent variable is ln(Z-score), Models 1 and 2 are baseline regression without and with the fixed effect respectively. Models 3 and 4 add control variables without and with the fixed effect respectively. Robust t-statistics are in parentheses. $*$, $**$, $***$ denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Dependent variable:		Ln(Z-score)		
TDR	-0.307	-1.075***	-0.269	-1.084***
	(-0.95)	(-3.01)	(-0.89)	(-3.28)
lnSize			0.189***	-0.434***
			(10.77)	(-3.26)
Diversity			-0.399***	-0.394***
			(-3.26)	(-2.89)
Ownership			-0.000	-0.003
			(-0.02)	(-1.41)
lnGDP			0.168***	1.927***
			(4.69)	(7.50)
Cons	4.72***	5.49***	-1.722***	-2.429*
	(14.43)	(15.28)	(-2.65)	(-1.69)
Bank fixed effects	No	Yes	No	Yes
Observations	1181	1181	1181	1181
R-squared	0.0008	0.0086	0.1402	0.1616

Table 4.5: Inflection point of technology.

This table reports OLS regressions of the relation between the technology development ratio (TDR) and risks over the 2009–2020 period. The samples are divided into four groups in accordance with the TDR quartile. The dependent variable is ln(Z-score); Models 5 to 8 add the fixed effect. Robust t-statistics are in parentheses. *, **, *** denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	lnZscore							
	25%	50%	75%	100%	25%	50%	75%	100%
TDR	1.722**	4.747	-4.826	0.322	1.479	2.548	-3.261	0.420
	(1.97)	(1.08)	(-1.12)	(0.52)	(1.39)	(0.48)	(-0.71)	(0.57)
lnSize	0.226***	0.225***	0.218***	0.080**	-0.305	-1.105***	-0.248	-0.676**
	(7.55)	(6.14)	(5.56)	(2.17)	(-1.03)	(-3.14)	(-0.69)	(-2.15)
Diversity	-0.014	-0.152	-0.573**	-0.691***	0.299	-0.276	-1.131***	-0.559*
	(-0.06)	(-0.64)	(-2.26)	(-2.69)	(0.93)	(-0.82)	(-3.59)	(-1.72)
Ownership	0.000	0.001	-0.001	0.001	-0.004	-0.002	0.001	0.006
	(0.21)	(0.56)	(-0.38)	(0.34)	(-0.70)	(-0.26)	(0.09)	(0.08)
lnGDP	0.177**	0.222***	0.132**	0.109	1.973***	3.127***	1.778***	2.16***
	(2.56)	(2.97)	(1.82)	(1.47)	(3.15)	(4.35)	(2.66)	(3.93)
Cons	-4.481***	-8.341**	2.692	1.195	-8.939***	-0.943**	-3.322	-0.189
	(-4.10)	(-1.89)	(0.60)	(0.88)	(-2.78)	(-0.17)	(-0.59)	(-0.05)
Bank fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
Observations	295	295	295	295	295	295	295	295
R-squared	0.2446	0.1944	0.1496	0.0591	0.1704	0.1555	0.2528	0.1471

Table 4.6: Impact of technology on bank risk by bank types.

This table reports OLS regressions of the relation between the technology development ratio (TDR) and risks over the 2009–2020 period. The samples are divided into three groups by bank types. The dependent variable is ln(Z-score); Models 5 to 8 add the fixed effect. Robust t-statistics are in parentheses. ∗, ∗∗, ∗∗∗ denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:			lnZscore			
	State-owned banks		Joint-stock banks		City commercial banks	
TDR	-3.088**	-3.444**	-0.952	-1.092	-0.007	-0.868**
	(-2.55)	(-2.49)	(-1.36)	(-1.59)	(-0.02)	(-2.21)
lnSize	0.554**	-0.618	0.299***	-0.201	0.283***	-0.481***
	(2.02)	(-0.31)	(3.55)	(-0.51)	(9.43)	(-3.19)
Diversity	-0.634	-0.376	-0.990**	-0.558*	-0.298**	-0.285*
	(-1.29)	(-0.66)	(-3.32)	(-1.77)	(-2.07)	(-1.75)
Ownership	-0.013*	-0.010	0.001	-0.008	0.000	-0.003
	(-1.89)	(-0.41)	(0.47)	(-1.28)	(0.13)	(-0.84)
lnGDP	0.452	1.802	0.131**	1.935***	0.147***	1.943***
	(1.26)	(0.83)	(1.13)	(2.62)	(3.83)	(6.39)
Cons	-11.942*	9.932	-3.678	-7.975*	-4.223***	-2.002
	(-1.74)	(0.26)	(-1.43)	(-1.69)	(-4.83)	(-1.33)
Bank fixed effects	No	Yes	No	Yes	No	Yes
Observations	66	66	142	142	973	973
R-squared	0.4256	0.4305	0.2146	0.3966	0.1049	0.1119

Table 4.7: Robustness tests with alternative risks.

This table reports OLS regressions of the relation between the technology development ratio (TDR) and risks over the 2009–2020 period. The dependent variable in Models 1 to 4 is Stvd. ROA; Models 2 and 4 consider the fixed effect. The dependent variable in Models 5 to 8 is Equity/Asset; Models 6 and 8 consider the fixed effect. Robust t-statistics are in parentheses. $*$, $**$, $***$ denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:			Stvd. ROA				Equity/Asset	
TDR	0.058	0.156***	0.050	0.147***	-0.014	-0.346	-0.192	-0.423
	(1.26)	(3.19)	(1.16)	(3.07)	(-0.02)	(-0.62)	(-0.33)	(-0.82)
lnSize			-0.028***	0.024			-0.290***	-1.856***
			(-11.25)	(1.24)			(-8.70)	(-9.00)
Diversity			-0.07	-0.001			-1.250***	-0.827***
			(-0.39)	(-0.03)			(-5.38)	(-3.91)
Ownership			0.000	0.001***			0.006***	0.014***
			(0.61)	(3.15)			(2.62)	(3.29)
lnGDP			-0.025***	- 0.145***			0.079	4.370***
			(-4.99)	(-3.89)			(1.15)	(10.96)
Cons			1.089***	0.803***			14.812***	11.690***
			(11.08)	(3.86)			(11.99)	(5.25)
Bank fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1181	1181	1181	1181	1181	1181	1181	1181
R-squared	0.0013	0.0096	0.1308	0.0670	0.0000	0.0004	0.0721	0.1656

Table 4.8: Robustness tests with technological progress.

This table reports OLS regressions of the relation between the technological progress (TP) and risks over the 2009–2020 period. TP is estimated as the derivative of cost function with respect to time. The dependent variable is ln(Z-score); Models 2 and 4 consider the fixed effect. Robust t-statistics are in parentheses. *, **, *** denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Dependent variable		lnZscore		
TP	-2.195***	-2.252***	-1.266***	-0.761*
	(-11.83)	(-12.28)	(-6.15)	(-1.75)
lnSize			0.151***	-0.485***
			(8.19)	(-3.61)
Diversity			-0.251**	-0.304**
			(-2.05)	(-2.09)
Ownership			-0.000	-0.004
			(-0.20)	(-1.50)
lnGDP			0.114***	1.673***
			(3.12)	(5.47)
Cons			-0.678	0.291
			(-1.13)	(0.12)
Bank fixed effects	No	Yes	No	Yes
Observations	1181	1181	1181	1181
R-squared	0.1054	0.1260	0.1665	0.1554

Table 4.9: Impact of technology on bank risk with an interaction variable.

This table reports OLS regressions of the relation between the technology development ratio (TDR) and risks over the 2009–2020 period. The dependent variable is ln(Z-score); Model 4 adds the fixed effect. Robust t-statistics are in parentheses. *, **, *** denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)
Dependent variable:	Ln(Z-score)	
TDR	12.965***	9.908*
	(2.62)	(-3.28)
lnSize	0.694***	-0.034
	(3.67)	(-0.14)
TDR*lnSize	-0.504***	-0.417**
	(-2.68)	(-2.01)
Diversity	-0.394***	-0.380***
	(-3.23)	(-2.79)
Ownership	0.000	-0.003
	(-0.02)	(-1.11)
lnGDP	0.161***	1.956***
	(4.49)	(7.61)
Cons	-14.920***	-13.291**
	(-3.00)	(-2.37)
Bank fixed effects	No	Yes
Observations	1181	1181
R-squared	0.1447	0.1648

Table 4.10: Robustness tests with endogeneity-L.Risk.

This table reports the results of controls for the endogeneity of the technology development ratio (TDR) estimated by using the GMM model with the instrument one-period lagged explanatory variable L.Risk. The dependent variables are lnZscore, Stvd. ROA and Equity/Asset respectively. Models 2, 4 and 6 include the interaction variable TDR*lnSize. Robust t-statistics are in parentheses. *, **, *** denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	lnZscore	lnZscore	Stvd. ROA	Stvd. ROA	Equity/Asset	Equity/Asset
TDR	-0.624**	17.151***	0.023	-1.160**	-1.021*	-20.607*
	(-2.00)	(2.98)	(0.81)	(-2.04)	(-1.82)	(-1.74)
L.Risk	0.318***	0.290***	0.406***	0.406***	0.313***	0.317***
	(4.50)	(4.17)	(4.09)	(4.07)	(9.88)	(9.95)
lnSize	-1.292***	-0.690**	0.034	-0.004	-3.344***	-3.994***
	(-4.91)	(-2.25)	(1.02)	(-0.12)	(-11.37)	(-8.46)
TDR*lnSize		-0.668***		0.044**		0.735*
		(-3.04)		(2.11)		(1.71)
Diversity	0.088	0.141	0.031	0.027	0.012	-0.064
	(0.51)	(0.82)	(1.48)	(1.28)	(0.05)	(-0.29)
Ownership	0.000	0.000	-0.002*	-0.002**	0.008	0.007
	(0.06)	(0.12)	(-1.95)	(-1.99)	(1.05)	(1.03)
lnGDP	3.226***	3.402***	-0.107*	-0.117*	6.907***	6.727***
	(6.25)	(6.62)	(-1.70)	(-1.86)	(12.40)	(12.23)
Cons	4.596*	-13.147**	0.283	1.426**	22.974***	42.190***
	(1.76)	(-2.28)	(0.90)	(2.17)	(5.73)	(3.69)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	888	888	888	888	888	888
Wald chi2	223.72	204.68	99.05	101.53	346.56	382.98

Table 4.11: Robustness tests with endogeneity – TDR_{t-1}

This table reports the results of controls for the endogeneity of the technology development ratio (TDR). The instrument variable is one-period lagged TDR. Model 1 is the first stage of 2SLS, Models 2 to 7 are the second stage of 2SLS with different dependent variables: lnZscore, Stvd.ROA and Equity/Asset respectively. Robust t-statistics are in parentheses. ∗, ∗∗, ∗∗∗ denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	TDR First stage	lnZscore Second stage	lnZscore Second stage	Stvd. ROA Second stage	Stvd. ROA Second stage	Equity/Asset Second stage	Equity/Asset Second stage
TDR		1.871***	261.132*	-0.228**	-32.600*	1.379	161.457
		(2.61)	(1.87)	(-2.35)	(-1.81)	(1.21)	(1.04)
TDR_{t-1}	0.470***						
	(16.51)						
lnSize		0.203***	10.122*	-0.029***	-1.268*	-0.231***	5.893
		(10.35)	(1.90)	(-10.93)	(-1.86)	(-7.42)	(1.00)
TDR*lnSize			-9.889*		1.235*		-6.106
			(-1.87)		(1.81)		(-1.04)
Diversity		-0.430***	-0.211	-0.010	-0.038	-1.335***	-1.199***
		(-3.23)	(-0.80)	(-0.56)	(-1.11)	(-6.33)	(-4.11)
Ownership		-0.001	0.003	0.000	-0.000	0.003	0.005*
		(-0.56)	(1.14)	(0.56)	(-1.09)	(1.29)	(1.72)
lnGDP		0.182***	0.099	-0.029***	-0.018*	0.018	-0.033
		(4.61)	(1.24)	(-5.36)	(-1.79)	(0.29)	(-0.38)
Cons	0.533***	-4.322***	-263.823*	1.433***	33.835*	12.494***	-147.732
	(18.54)	(-4.18)	(-1.88)	(10.22)	(1.88)	(7.62)	(-0.95)
Observations	1047	1047	1047	1047	1047	1047	1047
Wu-Hausman test:		10.49	9.93	8.83	8.35	1.91	2.33
P-value		Reject at 1%	Reject at 1%	Reject at 1%	Reject at 1%	Not reject	Not reject

Table 4.12: Robustness tests with endogeneity –FinTech

This table reports the results of controls for the endogeneity of the technology development ratio (TDR). The instrument variable is an external technology factor- FinTech, constructed by the Institute of Digital Finance Peking University. Model 1 is the first stage of 2SLS, Models 2 to 7 are the second stage of 2SLS with different dependent variables: lnZscore, Stvd.ROA and Equity/Asset respectively. Robust t-statistics are in parentheses. *, **, *** denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	TDR First stage	lnZscore Second stage	lnZscore Second stage	Stvd. ROA Second stage	Stvd. ROA Second stage	Equity/Asset Second stage	Equity/Asset Second stage
TDR		35.571	-338.196**	-0.789	7.848	103.877	-983.659**
		(1.33)	(-2.10)	(-0.67)	(-0.75)	(1.36)	(-2.38)
FinTech	0.005						
	(1.05)						
lnSize		0.387**	-12.639**	-0.033***	0.268	0.243	-37.653**
		(2.53)	(-2.07)	(-4.85)	(0.68)	(0.56)	(-2.40)
TDR*lnSize			12.831**		-0.296		37.335**
			(2.10)		(-0.75)		(2.38)
Diversity		-0.221	-0.590**	-0.010	-0.002	-0.746	-1.818**
		(-0.46)	(-1.97)	(-0.47)	(-0.08)	(-0.55)	(-2.36)
Ownership		-0.020	-0.002	0.001	0.000	-0.052	0.000
		(-1.28)	(-0.79)	(0.81)	(0.78)	(-1.14)	(0.03)
lnGDP		0.144	0.253**	-0.025***	-0.027***	-0.026	0.293
		(1.06)	(2.54)	(-4.09)	(-4.21)	(-0.07)	(1.15)
Cons	0.974***	-42.011	335.525**	2.038***	-6.685	-100.754	997.750**
	(34.75)	(-1.40)	(2.09)	(1.53)	(-0.64)	(-1.18)	(2.42)
Observations	1094	1094	1094	1094	1094	1094	1094
Wu-Hausman test:		23.35	25.16	0.63	0.90	55.41	52.67
P-value		Reject at 1%	Reject at 1%	Not reject	Not reject	Reject at 1%	Reject at 1%

CHAPTER 5

Conclusion

This thesis provides important results concerning the effect of diversity on Chinese commercial bank risk in three separate articles.

Chapter 2 investigates the effect of diversity on Chinese commercial bank risk from corporatet diversity. The key findings unveil a nuanced panorama: the baseline outcomes highlight that asset diversity aligns with the agency risk hypothesis, while income diversity conforms to the diversification hypothesis. Remarkably, a discernible discrepancy emerges between listed and non-listed banks in their responsiveness to corporate diversity, corroborating the agency hypothesis. Specifically, listed banks exhibit heightened sensitivity to corporate diversity, a phenomenon attributable to the agency problem. In this scenario, the expansion pursuits of managers, driven by personal incentives, supersede the interests of shareholders, consequently amplifying the banks' exposure to risk. Notably, the impact of corporate diversity on non-"TBTF" (Too Big To Fail) banks takes a slightly divergent trajectory, yielding a marginal adverse effect on bank risk. To deepen the investigation, an innovative approach is undertaken: the introduction of geographical diversity as an interactive element with asset and income diversity. The intriguing result surfaces that geographical diversity might act as a mitigating factor against the risk-reducing potential of income diversity. This phenomenon could arise from the intricate interplay between various forms of diversification and their dynamic effects on risk mitigation. Subsequently, employing instrumental variables for added rigor, a robustness assessment underscores a positive correlation with lnZscore, further validating the initial findings. The instrumental variables analysis divulges a noteworthy insight: banks situated closer to China's economic epicenter display a heightened propensity for business expansion, shedding light on geographic determinants as drivers of strategic decisions.

Chapter 3 investigates the effect of board diversity on Chinese commercial bank risk. This endeavor introduces a novel variable, "board diversity," constructed by normalizing factors such as the proportion of female members, the standard deviation of board members' ages, and the HHI indices reflecting educational and financial expertise diversity. The conclusions drawn from this investigation advocate for the risk-mitigating potential of a diverse board composition. Intriguingly, this effect exhibits a heightened prominence within the realm of small banks, imparting a new layer of significance to the interplay between board diversity and bank size. A deeper dive into the findings reveals intriguing patterns through quantile regression analysis: demographic factors, such as gender and age, display an inverted U-shaped relationship with risk, while cognitive attributes like educational background and financial expertise manifest a U-shaped dynamic. Moreover, the role of government representation on the board is probed, with outcomes indicating a limited impact on bank risk. Employing the fraction of board members simultaneously engaged in other firms as an instrumental variable, the outcomes seamlessly align with the established findings, reinforcing the pivotal role of board diversity in managing bank risk.

Chapter 4 investigates the effect of technology on Chinese commercial bank risk. The development of a novel variable, the "technology development ratio," through a sophisticated stochastic frontier model, forms the bedrock of this investigation. Initial results resonate with the agency hypothesis, reflecting a tug-of-war between senior managers' pursuit of personal gains and the potential benefits of technological progress. However, an intriguing dichotomy surfaces when analyzing banks with below-average technological capabilities and those with cutting-edge technology. For the former, technology development aligns with the efficiency hypothesis, enhancing risk management efficiency. Conversely, for the latter, the findings mirror a dominance of the efficiency hypothesis, accentuating the role of technological prowess in risk mitigation. Of note, the adverse impact of technology development on state-owned banks exceeds that on city commercial banks by a factor of four, painting a distinct risk landscape for different bank types. Robustness tests illuminate additional dimensions: past risk levels of banks emerge as facilitators of enhanced risk management, and historical technology levels continue to fuel technological innovation and risk assessment capabilities. Intriguingly, the specter of external FinTech looms large, exerting a dual impact on bank risk. While FinTech collaborations, in the absence of regulatory rigor, amplify risk exposure, they also carve out a segment of the bank's business, thereby diversifying risk sources.

In summation, these chapters collectively illuminate the multifaceted landscape of risk management in Chinese commercial banks, where factors like corporate diversity, board composition, and technological prowess interact in intricate ways to shape the risk profiles of these financial institutions.

However, there are also limitations in this thesis. For example, because of data availability, rural commercial banks are not considered. Regarding to risk measurement, we consider Z-score, NPL ratio. There are also other risk measurement, such as credit rating, which can be discussed in the future when the credit rating data is available. Moreover, the future research can also focus on non-bank financial institutions, micro financial institutions and other industries such as automobile and energy.

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