Income Diversification of Chinese Banks: Performance, Risk and Efficiency

QU, ZHIXIAN

Durham University Business School

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Zhixian Qu

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Department of Economics and Finance

Durham University Business School

University of Durham

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To My Parents

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Z. Qu

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Zhixian Qu **PhD (Economics)**

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Abstract

This research contributes to the debate on the effects of diversification in the banking industry, and provides a comprehensive analysis of how the diversification-performance, diversification-risk and diversification-efficiency nexus are affected when banks move into non-traditional businesses.

The research first examines to what extent income diversification can affect performance in the Chinese banking industry in terms of profitability. Results showing that in the Chinese banking sector as a whole there exists a diversification discount, suggesting that a shift from traditional banking business to mixed business lines negatively affects bank performance.

Following the discussion of profitability, we move the focus to the issue of stability. By adopting the first-differenced GMM estimator for the dynamic threshold panel data model, we get results showing that there exists an inverse U-shaped relation between diversification level and risk in the Chinese banking industry. Income diversification will reduce bank risk only after the bank has passed a certain threshold of income diversification. This pattern of relationship seems to be driven mainly by the learn-by-doing effect and the mitigation of agency problems, which result from the expansion of non-interest activities.

Finally, this thesis analyses the efficiency implications of the trend towards greater income diversification. We use a two-step approach by adopting within maximum likelihood estimation (WMLE) and dynamic Tobit model to estimate banks' efficiency scores and regresses those scores with banks' diversification indicators. We find that for the overall Chinese banking sector, income diversification has an efficiency-destroying effect.

This thesis provides a good reference for bank managers and policy makers to better understand and treat non-interest income in China's banking market. Our results also have fundamental and useful implications for bank managers and policy authorities seeking to enhance the performance and efficiency of Chinese banks under the condition of maintaining financial stability in Chinese financial system.

Declaration

The content of this doctoral dissertation is based on the research work completed at Durham University Business School, UK. No material contained in the thesis has previously been submitted for a degree in this or any other university.

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Chapter 1 Introduction

This chapter begins by giving an overview of the classification and channels of income diversification in the Chinese banking market. Then, it outlines the main motivations of the thesis, and the research questions to be addressed. After briefly noting the principal findings and potential contributions of this research, the chapter concludes by giving an outline of the composition and organisation of the whole thesis.

Chapter 1

Introduction

Banks traditionally derive their income through providing deposit and loan services. In the recent three decades, however, the global banking industry has experienced a profound change in their business modes. Banks in both mature and developing markets have shifted from their traditional deposit and loan businesses towards non-traditional and fee-based businesses. As a result, the shares of non-interest income in their total revenue have steadily increased. The main factors driving the change are regulatory changes and the changing environment for the banking markets (Allen and Santomero, 2001). Other contributing factors include financial liberalization, demand from savers for varied services and advances in technology (Meslier et al., 2014; Williams, 2016).

Changes in the business modes of global banking industry have been on a scale experienced by few industries and its consequences have been wide ranging. With banks shifting away from their traditional income sources to expand into new financial service lines, it is now commonplace for banks to increase the proportion of non-interest income through, for example, underwriting securities, insurance agency and foreign exchange trading services with high leverage and fewer capital restrictions (Mercieca et al., 2007; Sawada, 2013; Lee et al., 2014). The resulting implications are huge and the situation calls for greater research efforts to understand the bank diversification process and its consequences.

While some investigations have emerged with regard to mature and developing market, research on China that is currently the largest banking market of the world has been scarce (Zhou, 2014). This thesis aims to provide a novel perspective on the development of income diversification in the Chinese banking sector. The research is to focus on the effects of diversification on profitability, risk exposure and efficiency of Chinese banks.

1.1 Motivation and Research Questions

In an environment of increasingly tight capital regulation and fierce competition, diversification has become an important avenue for banks to develop new income in the mature market (Amidu and Wolfe, 2013). With the adoption of the diversification strategy, these banks have vigorously engaged in a wide range of financial products other than traditional ones. These include securities, insurance, trusts, and other financial categories. Over time, their non-traditional business has developed to become an important source of bank revenue, even in some cases exceeding traditional interest income.

The process of income diversification has blurred the boundaries between banking and other financial institutions. It has provided banks with the incentive to allocate resources to more profitable activities, which consume less capital but involve high levels of leverage, thus leading to the increase in banks' exposure to specific and systemic risks and causing inefficiency in resource allocation (Elsas et al., 2010; Brighi and Venturelli, 2013). In detail, Wagner (2010) claims that limited liability incentivizes both bank managers and shareholders to allocate and diversify their portfolio towards correlated assets, and to ignore the risk of joint failures in the banking system brought about by raising bank exposure to common sources of risks. However, such an incentive to managers to over-diversify will in turn harm the stability and allocation efficiency of the wider financial system, because diversification makes institutions more similar to each other, thus exposing them to the same risks, and increasing the probability of joint failure (Acharya et al., 2006). Therefore, following the global financial crisis of 2008, the international banking industry has taken steps to implement more prudent management of diversified businesses, and regulators have introduced regulatory changes to improve banking supervision (Delimatsis, 2012; Zhu and Chen, 2016).

China's banking industry has also experienced the significant rise and development of non-traditional business (Zhou, 2014). This has taken place against a background of acceleration of financial reforms such as interest rate liberalization, banking system reform, and internationalization of the Chinese currency. Increasingly strict capital supervision and financial disintermediation driven by the rapid development of the capital market are forcing Chinese banks to look beyond traditional commercial banking services and to search out new income sources; hence banks are gradually moving away from a single income structure that relies largely on interest income, to a more diversified income structure (Xiongbing and Wei, 2016). In the circumstances, Chinese banks have also shifted their focus away from on-balance sheet business to off-balance sheet business, and to allocate their portfolios more highly leveraged and high-yield assets with fewer regulatory capital requirements and activity restrictions (Qu et al., 2017).

Chinese banks' shift to income diversification is still ongoing. While they continue to rely on net interest income, their non-interest income from non-traditional businesses has start to emerge and is growing. The incipient proportion of non-interest income in their total income is relatively small and they have less professional expertise in dealing with the uncertainties inherent in high-leverage activities (Iskandar-Datta and McLaughlin, 2007 Barth et al., 2013; Alhassan and Tetteh, 2017). Given the transitional nature of China's financial reform and deregulation of non-interest activities, it is inevitable that the process of diversification and its effects on Chinese banks would have unique characteristics compared to that of banks in other markets. Consequently, it is necessary to investigate the effects generated from income diversification of banks in China, including their profitability, risk exposure and efficiency when pursuing the diversification strategy.

In this thesis, Chinese banks are divided into three sub-groups, according to their level of systemic importance. They are global systemically important banks, national systematically important banks and other banks. Our investigation is focused on the effects of income diversification in three aspects, namely the effects on banks' profitability, risk level, and efficiency. By employing a range of empirical techniques across different sub-samples, we attempt to answer the following research questions:

1. What are the driving forces behind the transformation of income structure in China's banking industry? Specifically, under the conditions of financial reform and changes in the macroeconomic environment, why do banks have raised their investing in non-interest income?

2. Whether or not the diversification of income structure improves the performance of banks in China?

3. To what extent income diversification increases banks’ exposure to risk, with regard to bank-specific risks and financial distress? In particular, does there exist a non-linear relationship between Chinese banks’ risk exposure and their diversification levels, and if so what is the threshold and optimal level of non-interest activities for diversified banks to minimize their risk?

4. Several studies have considered banks' profitability and efficiency together, thus leading to confusion and to a range of inconsistent and contradictory empirical results. This thesis considers these two aspects separately, asking: Does diversification have the same effect on both profitability and efficiency? Could the process of income diversification increase bank profits, while at the same time causing a reduction in internal efficiency?

1.2 Main Findings and Contributions of the Thesis

In order to explore these questions, this thesis first provides an in-depth analysis of the background to and causes of the changes in the income structure of China's banks. The driving forces behind Chinese banks' shift to non-traditional business include development of financial reforms, the changing macroeconomic environment, maturing of financial regulations and increasing competition in the banking market (Amidu and Wolfe, 2013; Luo, 2017; Borio et al., 2017; Okazaki, 2017).

Having provided the background, the thesis then moves to focus on empirical evidence of the effects of diversification on Chinese banks. In the empirical exercises throughout the thesis, major Chinese banks are categorized into three groups, namely global systemically important banks (G-SIBs), domestic systemically important banks (D-SIBs) and other banks (N-SIBs). The first empirical chapter investigates whether income diversification is beneficial to the returns and overall performance of the banks.

Dynamic panel data models are employed for the empirical investigation. Evidence shows that for the Chinese banking sector as a whole, income diversification has a negative effect on the overall performance; however, the effects of diversification vary among banking groups. While Chinese G-SIBs gain significant benefits from diversification, but such benefits are non-significant for D-SIBs, and diversification has a negative effect for N-SIBs.

The differentials of the diversification effects on banks' performance are attributable to bank-specific characteristics. In general, large-sized and more diversified banks are better able to benefit from income diversification, which is consistent with the results of Gurbuz et al. (2013), Köhler (2014) and Chen and Zeng (2014). Performance improvements are more likely when banks operate with good institutional governance and under sound regulation. It is plausible that such an environment prompts banks to maintain a high level of the capital adequacy ratio and so could encourage managers to invest their limited funds in more profitable business, thus improves the banks' performance (Xia and Huang, 2017).

Next, the thesis investigates into the relationship between bank diversification and risk in China. The focus is on the changes to banks' idiosyncratic risks and financial distress at different levels of diversification. Evidence is found that for the overall Chinese banking sector, results reveal the existence of an inverse U-shaped relationship between bank risk and income diversification in terms of both banks' idiosyncratic risk and their financial distress. This is driven mainly by the learn-by-doing effect and by the elimination of agency and moral hazard problems with the banks' expansion of non-interest activities (Barry et al., 2011). Furthermore, the same methodology is also applied to three sub-groups, For Chinese G-SIBs, diversification has a significantly negative effect on banks' both idiosyncratic risk and financial distress. For D-SIBs and N-SIBs, the effects again exhibit an inverse U-shape. The results may be explained by different income structures and risk preferences among the banks. Significant results are also obtained when decomposing the non-interest activities into three components, namely fee-based, trading and other income activities (Valverde and Fernández, 2007; Köhler, 2014), and by utilizing three different measures of risk, i.e. credit, liquidity and interest rate risk.

Finally, we consider the effect of diversification on bank efficiency in China. First, bank efficiency scores, in terms of both cost and profit. Second, the investigation employs the dynamic Tobit model to examine unobserved, time-invariant bank heterogeneity. For the overall Chinese banking sector, income diversification has an efficiency-destroying effect. This outcome is consistent with Cheng (2015); however, the effects vary among the banking groups. For Chinese G-SIBs, diversification has a significantly harmful effect on both cost and profit efficiency. For D-SIBs, the effects are similar, but the discount magnitude is smaller. For N-SIBs, diversification however has a positive effect on the efficiency level. When decomposing the non-interest activities into three components, fee-based and other activities impose a discount on banks' efficiency, whereas trading activity results in efficiency improvements for all three sub-groups.

The existing literature is limited in its research scope, and this thesis extends the literature in an important way. Most existing studies focus on mature markets, for example Lepetit et al. (2008), Elsas et al. (2010), Boot and Ratnovski (2012), Nguyen et al. (2016), and Maudos (2017). Only a small, albeit expanding, body of the literature explores the emerging markets, China in particular. However, compared with the markets in mature and other emerging countries, the Chinese banking industry and regulatory system exhibit a number of unique features. It is these differences that provide the motivation for this study to investigate the income diversification effects in China. In doing so, this thesis makes several original contributions to the literature.

Compared with the mature market, the scale and business scope of the Chinese banking industry is very concentrated and uneven; more specifically, the Chinese big-four banks control 67.9% of the overall assets of the entire Chinese banking industry (CBRC, 2016). Therefore, the Chinese banking sector can be characterized as an oligopolistic market (Edirisuriya et al., 2015). This characteristic has had a major impact on the form of business expansion in China's banking industry, and has also formed a different diversification motivation compared with mature and other emerging markets, where the main motivation for diversification is considered to be profitability.

First of all, currently, interest income occupies a large proportion of the income stream of Chinese banks. However, given continual shrinking of the interest margin, combined with the Chinese financial reform and regulatory restriction, in this oligopolistic market banks are driven to find alternative ways to use their market power to make up the loss by binding together their lending and non-interest activities, such as fee and commissions. Therefore, in the Chinese banking market the motivation for income diversification is pretty different from that in other markets. Consequently, it is worthwhile to investigate whether or not the composition of the market and the motivation for diversification could lead to different diversification effects on banks' performance and risks. In the Chinese case in particular, these questions merit a separate and dedicated study.

Secondly, the liberalization reform of the Chinese banking system, in particular the relaxation of the access mechanism for capital injection from both foreign and private capital, has created a competitive market atmosphere. Such capital injection supplies technological spillover to the Chinese banking sector and increases the incentive for banks to provide more financial services and to seek the potential benefits from product innovation and diversification. Against this background of changing market ownership structure and the increasing complexity of banking products, it is necessary to investigate the Chinese banking market and to find out how these changes will impact on banks' performance and risk indicators.

Thirdly, compared with other markets, the Chinese banks suffered less negative impact during the global financial crisis. This could be attributed to the Chinese government's special policy schemes for the banking industry, for example the provision of potential non-performing asset protection, whereby the state-owned asset management companies can help banks to divest non-performing assets; and 'disguised' funding through the Huijin Investment Company, which is undertaken by the Ministry of Finance. However, such potential government guarantees not only protect banks from financial crisis, but can also increase agency costs and the too-big-to-fail problem. Consequently, the expansion of banks' business lines, especially the extension of non-interest business combined with high leverage carries much higher risk than the same activities in other markets. Therefore, this thesis makes a comprehensive analysis of the development of income diversification in the Chinese banking market in the context of extensive financial reform and regulatory and macroeconomic changes.

Furthermore, the channels through which banks can expand their non-interest activities are different in China than that in other countries. In the US banking market, a system of bank holding companies has been constructed to facilitate income diversification, while Germany has adopted a universal bank system. However, in the Chinese banking sector these two systems co-exist; that is, state-owned banks and national joint stock banks apply the bank holding companies mechanism, where banks establish or merge with financial intermediates to develop their non-interest activities, while other medium and small non-systemically important banks adopt the universal banks mechanism whereby they establish multiple departments within the bank to develop cross-selling business strategies. This mixed development model is a new path that China has chosen in the early stages of diversification. It involves different risk management strategies and the corresponding affordability across different types of banks, hence requires different diversification direction and strategies.

In addition, most of the studies conducted about the emerging markets have focused on cross-country datasets (e.g. Gamra and Plihon, 2011; Sanya and Wolfe, 2011). However, the Chinese banking market has unique features, and should therefore be investigated separately from the emerging market set. Most notably, the scale of the Chinese banking market is now among the largest worldwide: according to the China Banking Regulatory Commission and the World Bank, in 2018 the total assets of China's banking institutions were 260 trillion CNY (around USD 38 trillion), while the corresponding amount for the Eurozone was USD 31 trillion, and for the USA USD 16 trillion. Clearly, therefore, it is inappropriate to investigate the Chinese market alongside other emerging countries, such as Mexico, Philippines or Thailand, where the magnitude of the market is considerably lower.

Finally, unlike banks in other emerging countries, Chinese banks maintain more interconnectedness with the global banking sector. Here, the label of systemically important banks describes the scale and degree of influences those banks hold in global and domestic financial markets. Currently there are 29 global systemically important banks, of which 13 are in Europe, eight in the US, three in Japan and one in Canada. For the emerging markets, there are only four globally systemically important banks, all of them in China. Therefore, the stability of the Chinese banking sector is of critical importance to the global market. Any credit default in China would likely start a chain reaction and cause systemic risk in the global market. It is therefore highly relevant that in recent decades the Chinese banking market has seen an ever increasing growth rate in the expansion of non-interest income; indeed, in 2011, the growth rate of non-interest income reached a high point of 61.9% (CBRC). This rapid growth rate is rare in other markets, and brings with it greater uncertainty and other potential factors that could affect the stability of the Chinese market. This makes it particularly important to study the impact of changes in non-interest income in the Chinese market from multiple perspectives, namely those of the banks' managers, of regulators, and of the stability of the international financial market.

More importantly, in order to avoid the replication of techniques employed in the research of developed markets, this thesis also applies several improved methodologies to address bank diversification in the specific context created by China's unique institutional background and data characteristics.

First, in the mature banking market, banks have accumulated sufficient information, techniques and risk management ability to deal with the specific risks generated by the non-interest activities. However, based on the learn-by-doing effect theory, given that Chinese banks only received permission to embrace non-interest activities in 2005, and that the development of non-interest income in the Chinese banking market is very uneven across different banks, it is likely that the relationship between diversification and risk in China is non-linear and follows a dynamic process (Gamra and Plihon, 2011), rather than being static in nature as in mature and other emerging markets.

This implies that static and linear methods could be inadequate to capture the risk implications of diversification in the Chinese banking market and to estimate the diversification effect on banks' risk level. Rather, an improved methodology, namely a dynamic threshold model, would be more appropriate to give a clear estimation of the non-linear relation between income diversification and risk, which evolves with the development of banks' engagement in diversification. As such, a GMM-type threshold model is what is required. Therefore, this thesis adopts the first-differenced GMM estimator for dynamic threshold panel data model.

This research is the first to adopt the above approach to test the learn-by-doing effect in the Chinese banking market. The improved method could help to estimate the potential inverse-U shaped correlation during the diversification process. Compared with traditional static threshold estimation, it has the advantage of giving a dynamic view of the diversification effects on bank risk while avoiding the bias from the quadratic terms used in some previous studies on non-linearity in the banking markets (Bun and Windmeijer , 2010; Hsiao and Zhang, 2015). The model also overcomes the problems associated with previous GMM-type threshold models (such as Ramírez-Rondán, 2015), whereby both regressions and threshold variables have to be exogenous. More importantly, this dynamic threshold estimation could address the endogeneity problem that has been associated with Chinese banking market research, as noted by several previous studies (Acharya et al., 2006; Stiroh and Rumble, 2006; Baele et al., 2007).

Another important methodology improvement relates to stochastic frontier analysis (SFA), which is usually considered an appropriate tool to investigate the efficiency implications of diversification (Rezitis, 2008; Beccalli and Frantz, 2009; Cheng, 2015). In this thesis, two issues have been identified and resolved to improve upon the SFA used in the mature market research. First, since the efficiency score generated from SFA falls in the interval [0, 1], it is necessary to model the SFA response properly. Related studies in the mature market generally adopt a static panel data model using the OLS method. However, as the explanatory variable in the regression equation cannot be expected to have a normal distribution, neither can we expect the regression error term to meet the assumption of normal distribution. Consequently, the OLS method often leads to biased and inconsistent parameter estimates (Souza and Gomes, 2015). To address these problems, we use a Tobit estimation. In adopting the doubly censored Tobit model developed by Elsas and Florysiak (2015), this study is the first in the field to employ the dynamic estimation of such a model. This estimator addresses the inconsistencies generated from unobserved heterogeneity; furthermore, it allows the addition of a lagged dependent variable, thus providing a dynamic view. Unlike the similar estimation introduced by Loudermilk (2007), it is also applicable for unbalanced panel data, which is particularly important for this research given the restrictions on data collection in the Chinese case.

The second issue with regard to SFA is that, given the limited data available for Chinese banking studies, most of the research in this field faces a short panel problem. This leads to an incidental parameters problem, where the variance parameters for short panel data are more likely to be affected under traditional SFA and the fixed-effect SFA model proposed by Greene (2005) and commonly used in the previous literature. Therefore, following Chen et al. (2014), this thesis solves the problem by adopting within maximum likelihood estimation (WMLE), which relies on the within transformed model using the standard maximum likelihood method. This thesis represents the first use of WMLE in studying the Chinese case.

Finally, the existing literature in this field suffers from a lack of rich analysis. To enrich the analysis and hence ensure the robustness of the research, this thesis utilizes a large set of banks' indicators to describe banks' characteristics. Previous studies, especially those focusing on the Chinese banking industry, utilize only accounting-based measures to assess the diversification effects (e.g. Lepetit et al., 2008; Hsieh et al., 2013). Consequently, the results obtained are not particularly sound or robust. In contrast, this thesis divides non-interest income into three sub-categories, and investigates efficiency from two perspectives, namely cost and profit efficiency, separately. In addition, this thesis considers not only accounting data but also employs measures based on economic conceptualization, such as, in the case of risk analysis, both idiosyncratic risk and financial distress. Further, to assess the diversification implications for the management of different types of risk, the research takes into account different risk aspects, such as credit risk, liquidity risk and interest rate risk.

Consequently, this thesis is able to conduct a more comprehensive analysis of diverse aspects of the effects of income diversification on banks than has been possible in previous research.

1.3 Income Diversification in the Chinese Banking Industry: An overview

1.3.1 Classification of Diversification

For a commercial bank, a diversification strategy means a broadening of income sources, expansion of business scopes, and extension of operating activities. Generally speaking, diversification can be classified into three types, namely assets diversification, geographic diversification and income diversification, all of which have developed in line with technological advances, policy changes and customer demand (DeYoung et al., 2004).

Diversification of assets refers to different types of loans within the loan portfolio. Geographic diversification refers to expansion in terms of operational area, where banks set up branches in different regions or countries through establishment or acquisition, and provide financial products and services in local or wider regions to achieve cross-regional or multinational operations (Meslier et al., 2014). Finally, income diversification refers to those activities of banks that are beyond the scope or range of a single financial service product. This type of diversification is manifested by banks' ability to cross the boundaries of traditional commercial banks in product services and to provide customers with several or all of banking intermediation, securities, insurance, and trusts services (Schmid and Walter, 2009). Banks may also update and refine their credit business through financial innovation and may expand into intermediary businesses, securitization and various types of segmentation within each traditional service. With income diversification, banks no longer rely on a single source of income, such as traditional net interest income. Instead, they increase new income through diversified business lines, and diversify the income streams of different businesses through increased non-interest activities. This thesis focuses mainly on income diversification, and seeks to analyse its effects on Chinese banks.

1.3.2 Channels of Income Diversification

At present, there are two channels or business modes of diversification for banks in China. First, large-scale banks tend to adopt the bank holding group mode, which allows them to exploit their advantages in scale, outlets and customers to build a cross-market and diversified financial services platform (Peng and Hu, 2005). Banks build up platforms for non-traditional activities through acquisitions, holdings, or the establishment of financial leasing companies, trust companies, fund management companies, insurance companies, and other non-bank financial institutions in both the domestic and overseas markets. Meanwhile, financial companies can enter the banking market and establish financial holding groups. Currently, among the main players in the Chinese banking market the Everbright Group, CITIC Group, Ping An Group, and Shanghai International Group hold a full license to have access to all financial services in China, and are the owners of, or majority shareholders in, the China Everbright Bank, China CITIC Bank, Ping An Bank, and Shanghai Pudong Development Bank, respectively.

Second, in an environment of strict financial restrictions, many medium and small-sized commercial banks are turning their attention to cooperation with trust, security, fund insurance and other non-banking financial institutions (Hachem and Song, 2015). Under the widely adopted pattern of bank-trust cooperation, the bank sells the issued wealth management products to investors, and the funds raised are passed to the trust company. Then the trust company invests the funds in a company designated by the bank. As regulations concerning such cooperation were tightened since 2009, banks have started to look for cooperation with other financial institutions. First of all, bank-security cooperation is aimed at transferring credit assets (mainly bill assets) to off-balance sheets (Lu et al., 2015; Xu, 2017). Here, banks use wealth management funds to purchase securities companies' asset management plans, and use the latter to put funds into designated projects to avoid the constraints of the loan-to-deposit ratio control and credit scale imposed by the Chinese regulator. Bank-insurance cooperation in China follows an agency sales model, where commercial banks sell insurance products on behalf of insurance companies, and in return receive commission income (Haifeng, 2011).

1.3.3 Income Diversification Activities

For banks, income sources can be divided into interest business and non-interest business (Mamun and Hassan, 2014). Interest business is business related to the bank's net interest income and includes traditional deposits and loans businesses. Non-interest income refers to all income other than that from loans and securities business.

According to Chinese regulations, the non-interest income of banks consists of five parts: net fee and commission income, investment income, fair value exchange income, exchange gains, and other business income. A large proportion of non-interest income is generated from fee-based activities; that is, it is revenue obtained by charging customers for certain financial services. This includes, among others, monthly service fees for trading accounts, commissions for insurance coverage for homes and businesses, membership fees for the acceptance and use of certain types of credit cards, and income from financial consulting services for individuals and companies. Fee income can be further classified into two main categories: that originating from the traditional business and services of commercial banks, such as cheque and savings account fees, machine usage fees, and fees and commissions for providing loans to customers; and that originating from, and expanding with, non-traditional businesses, such as fees and commissions for investment banking services, trading products, investment products such as stocks, bonds and mutual funds for clients, and service fees for providing wealth management services for the customers through affiliated trust company departments.

In short, bank diversification in China means banks diversify their income sources and continually expand their scope of financial services, increase the proportion of non-interest income in the total revenue through, for example, underwriting securities, securitization and foreign exchange trading services with financial innovation and higher financial leverage (Laeven and Levine, 2007; Doumpos et al., 2016).

1.4 Theories on Income Diversification: An overview

Several theories have been proposed to explain the effect of bank diversification, and whether this brings benefits or discount to banks' performance, risk and efficiency. According to Boot (2003) and Meng et al. (2017) diversification can be treated as a strategic response to business uncertainty. Hence, most studies in this field are based on the modern portfolio theory and suggest a risk separation effect, thus giving a positive view of the diversification effect on banks' efficiency. Further, several scholars highlight that diversification can help banks to gain benefits through improved informational advantages (Akhigbe and Stevenson, 2010), increased the market power (Palich et al., 2000), the construction of an internal capital market

(Pitelis, 2007), and economies of scale (Drucker and Puri, 2008). However, other researchers claim that there is a diversification discount, whereby the benefits pointed out by portfolio theory might be eliminated by the presence of asymmetric information (Shen and Lee, 2006), moral hazard and agency problems (Freixas et al., 2007), rent-seeking behaviours (Datta et al., 2009), high-intensity market competition, and joint failure under the condition of business homogenization (Acharya et al., 2006). Finally, owing to the learn-by-doing effect (Lou, 2008), diversification might exhibit a non-linear relationship with banks' performance.

1.4.1 Modern Portfolio Theory

Portfolio theory, the most widely used theory to explain banks' diversification activities, suggests that increasing the proportion of non-interest income can provide a potential risk reduction. Modern portfolio theory indicates that concentrated revenue streams adversely impact banks' revenue volatility, and that a strategy of income diversification could generate a coinsurance effect (Lewellen, 1971; Tong, 2012). As suggested by Mooney and Shim (2015), the coinsurance effect would decrease the volatility of future cash flows for the diversified bank, and make conglomerates less sensitive to the risk taking by a single division. Therefore, banks should improve their stability and disperse idiosyncratic risk through portfolio diversification.

Moreover, as argued by Ibragimov et al. (2011), the portfolio theory also suggests that each bank could form a joint mutual market portfolio, whereby each bank would contribute its risky portfolio to the total and receive back its proportional share. In the situation where there was sufficient variety of risk classes, various idiosyncratic risks under individual portfolios would be eliminated. This would result in a more resilient, and more effective, banking system.

More importantly, in addition to risk reduction, previous research indicates that in a portfolio, non-interest and interest incomes can be mutually beneficial (Pennathur et al., 2012). As suggested by Stiroh (2004), the lending business provides a channel for banks to attract clients to their non-interest activities, as people are more likely to seek fee-based services in the same bank. Wagner (2010) shows that banks are keen to adopt a strategy that uses attractive lending and deposit rates to improve customer stickiness and to make themselves more profitable through high-return non-interest income. Therefore, traditional activities could provide the high-quality and essential clients for high-return non-interest activities, while the non-interest activities could stimulate banks' innovation and satisfy customers' financing demand in order to further establish customer stickiness (Acharya et al., 2006; Lepetit et al., 2008).

1.4.2 Informational Advantages

Diversified banks can obtain superior information from their mixed business lines. According to the theory of financial intermediation, such information advantages represent a further benefit of diversification. More specifically, information is considered an important input factor to impact banks' efficiency and reduce banks' specific risk with regard to credit screening and customer relationship (Diamond, 1984; Bencivenga and Smith, 1991; Saunders and Walter, 1994; Elyasiani and Wang, 2012).

First, with the increase in informationally intensive assets and financial services, banks gain comparative advantages whereby they can capitalize on client information obtained when they process loans, thus offsetting the excessive credit risks generated from non-interest income, and improving their operational efficiency (Elsas et al., 2010). Where there is integration of lending and non-traditional activities, multiple financial products are sold to similar customers. In this situation each business line could reap benefits from the access to private information and thus reduce the uncertainty associated with the lending relationship (Mercieca et al., 2007).

Further, lending business can offer benefits to securities underwriting, as it can contribute to reducing uncertainty; thus the fee-based activities may compensate for pricing risks (Petersen and Rajan, 1995). Similarly, the underwriting business can feed back credit and liquidity information to the lending business, as banks often hold equity from borrowing companies and sit on the supervisory boards of those firms (Dietrich and Vollmer, 2012). Such advantages in relation to non-public information can smooth the financing channel between banks and enterprises. There will also be a reduction in the potential risk through repeated interactions over time, and through the banks' intense monitoring of the companies' expansion strategies (Elsas, 2005).

Second, improved information from income diversification within intermediary business could also reduce financial frictions between borrowers and lenders, thus helping banks to overcome asymmetric information (Akhigbe and Stevenson, 2010) and gain improved capital financing (Klein and Saidenberg, 2010). Pyle (1971) suggested the important interaction between companies' assets and liabilities, in which asymmetry of information between borrowers and lenders would largely impact on banks' efficiency characteristics. Diamond (1984) developed a model in which banks could overcome the problem of asymmetric information and improve overall efficiency through mergering with other financial intermediaries; as a result, mature financial intermediation is more likely to minimize the cost of monitoring, which will prove useful to reduce incentive problems between borrowers and lenders.

1.4.3 Market Power Theory

Market power theory, introduced by Porter (1981), proposes a set of strategies to access market power and release market competition. One important strategy is diversification across different markets (Barney, 2002). Diversified business can help banks gain competitive advantages in other financial markets, and access market power due to cheap capital funding. Firms entering a new market can use their resources in other markets to support and strengthen the new business. Thus, according to Shin and Stulz (1998) and Barney (2002), business expansion to non-interest activities could increase banks' market power and enhance competitive advantages by providing better investment opportunities, and offer lower financing cost supported by their business in other markets. Diversified banks could concentrate funds and invest in less competitive markets in order to control the market prices, prevent potential competitors from entering the industry, and maintain a better performance level (Palich et al., 2000).

1.4.4 Resource Based View Theory

Based on the transaction cost theory established by Coase (1937) and Williamson (1975), several studies have argued that expansion of the number of types of financial services through the construction of financial conglomerates will help firms to overcome a number of financial problems (e.g. Leff, 1978; Hitt et al., 2006). In particular, conglomeration may help member firms to construct an internal capital market and to overcome market imperfections that are prevalent in emerging economies (Khanna and Palepu, 2000; Kogut et al., 2002; Wan and Hoskisson, 2003;

Wan, 2005). Therefore, resources integration is an important consideration for banks embarking upon a strategy of diversification.

With regard to resources integration, the resource based view (RBV) (Penrose, 1959), emphasizes the importance of oligopolistic interaction and interfirm competition (Pitelis, 2007). In addition, as argued by Weston (1970), while focused-business companies can configure resources only through external capital markets, diversified companies are able to increase their effectiveness through access to an internal capital market and by transferring resources to higher profitability objectives, so-called 'winner-picking' (Lamont, 1997; Stein, 1997). Such a winner-picking effect could help banks to reallocate internal resources from less profitable sectors to more effective sectors (Stein, 1997).

1.4.5 Economies of Scale and Synergistic Effect

According to the economies of scale-based theory proposed by Sirri and Tufano (1995), the expansion of non-interest income can help banks to achieve operational synergies (Rezitis, 2008). The attainment of these synergies relies on scale economies (Stiroh, 2000; Akhigbe and Stevenson, 2010; Sanya and Wolfe, 2011). As argued by Drucker and Puri (2008), the expansion of non-interest business is largely based on banks' infrastructure, hence a mixed business line strategy could help banks to spread fixed costs and managerial overheads over an expanded product mix. Klein and Saidenberg

(2010) also suggest that, as several financial intermediaries under diversified banks can separate their contracts to share facilities and production technology, the average cost can be reduced and banks' profitability and performance can be increased.

In addition, scale economies may result in operational benefits, because cross-selling strategy companies that engage in merger and acquisition with mature financial intermediaries could share monitoring, advertising and account maintenance, thus further reducing operational cost and financial friction, and improving banks' production efficiency (Elyasiani and Wang, 2012).

1.4.6 Asymmetric Information

Because income diversification carries with it the potential problem of asymmetric information between a bank and its pool of borrowers, some scholars have argued that there is likely to be a diversification discount (Sanya and Wolfe, 2011). Krishnaswami and Subramaniam (1999) claim that the diversification process greatly increases the asymmetry of information. In addition, Liu and Qi (2003) suggest that diversified firms have insufficient and inadequate channels of information production and transmission to managers, thus reducing the quality of banks' investment decisions and causing inefficiency and value loss.

According to Drucker and Puri (2005), asymmetric information gained through combining lending and underwriting could mean that banks obtain an abnormal return from the securities industry; consequently, banks would have an incentive to underwrite securities of unsound companies and to place them on the financial market without disclosing their private information about the firms (Santos, 1998). In addition, due to the very large numbers of customers, banks may not be able to collect sufficient information. As a result, banks may fail to screen out potential bad borrowers, which could compromise banks' risk prediction and operational strategies, leading to an increase in financial instability (Abdelaziz et al., 2012).

1.4.7 Too-Big-to-Fail and Moral Hazard Problem

The expansion of business scale is also associated with the too-big-to-fail status, which offers a further explanation for the increased risk (Williams, 2016). That is, when banks become large enough to be deemed too big to fail, managers have incentives to accentuate the moral hazard, and therefore they may operate the banks in inefficient ways. According to Lin et al. (2012), banks with such moral hazard problems tend to keep large chunks of their resources in less profitable projects, thus causing inefficient allocation of their resources and increased risk. Furthermore, Rezitis (2008) argues that, once a company has achieved a certain scale, it faces inefficient monitoring and supervision across different banking sectors. Especially in emerging countries, banks enjoy invisible guarantees from central banks and governments. Consequently, during financial distresses, banks have incentives to expand high-risk but more profitable projects, which would lead to the accumulation of both specific and systemic risks within the banking system (Hellmann et al., 2000; Kaufman, 2014).

1.4.8 Agency Theory

The agency problem is raised by the conflict of interest between managers and shareholders (Martín-Reyna et al., 2012; Reyna et al., 2012; Kazemian and Sanusi, 2015). As argued by Jensen (1986) and Vogt (1994), compared with single-business companies, complicated business lines lead financial groups to over-investing in negative net present value projects, especially in the case where managers have excessive management power and large free cash flows. That is, managers tend to invest excess cash flow to increase income, rather than raise the cash payment to shareholders, and this behaviour tends to impair banks' performance and destroy value for shareholders. This is particularly so in the case of under-regulated economies such as China's, which also maintain a highly centralized management system. Under the circumstance, Freixas et al. (2007) suggest that managers might also abuse deposit insurance in order to refinance investment banking and other high-risk activities, which could lead to an excessive increase in the risk for the whole banking system.

With regard to the diversification-risk effect, the shareholders' value can be treated as the call option on the value of the firm exercised in circumstances where the value of the assets is greater than the debt claim (Van Lelyveld and Knot, 2009). Under the condition of risk reduction, shareholders' value would decrease. In addition, according to the managerial risk reduction theory introduced by Amihud and Lev (1981), although a company may reduce its investment risk through the construction of home-made portfolios, managers cannot diversify away their employment risk, for example in terms of professional reputation and job losses. Therefore, managers will naturally choose to employ cross-selling strategies, which would enhance their job security but at the cost of endangering the benefits of shareholders and the efficiency of the company.

Moreover, according to managerial entrenchment theory, managers who wish to increase the company's reliance upon them, and thus strengthen their own positions, are more likely to employ cross-selling strategies and make investments beyond the firm's value-maximization level (Shleifer and Vishny, 1989). This is because it is difficult for external investors to supervise a complicated mix of business lines, and in such a situation there will be few candidates who would be able to take over the manager's place (Scharfstein and Stein, 2000). Once those managers have too much controlling powers in the running of the bank, the interests of external investors will be further compromised due to the higher bonuses paid out to the managers along with the expansion of more profitable non-interest activities (Scharfstein and Stein, 2000). Such over-diversification can lead to inefficient portfolio construction and confusion within the bank operating system (Deng and Elyasiani, 2008).

1.4.9 Structure-Conduct-Performance (SCP) Paradigm

The structure-conduct-performance paradigm is an important theory to explain how the market structure determines the conduct of companies in the market, and then the feedback effects occur such that the company conduct also affects the market structure (Hannan, 1991; McWilliams and Smart, 1993; Panagiotou, 2006; Athanasoglou et al., 2008; Alhassan et al., 2016). In the Chinese banking market, the narrowing spread caused by interest rate liberalization, combined with the ongoing financial disintermediation, increases banks' willingness to diversify their business in order to broaden their sources of income. In turn, mergers and acquisitions among banks and financial intermediaries, and the consequent departure of banks from traditional business lines, serve to increase business similarities within the financial system and cause income convergence (Ibragimov et al., 2011). Consequently, the diversification process creates competitive pressures amongst financial conglomerates across a wide range of market segments. With regard to the intensely competitive Chinese banking sector, there are two main perspectives, namely the competition-stability view and the competition-fragility view.

According to the competition-stability view, a more intensely competitive environment could increase overall innovation and enhance operational management in the provision of services within the banking sector (Berger and Hannan, 1989; Acharya et al., 2006; Lepetit et al., 2008; Schaeck and Cihak, 2010; Turk-Ariss, 2010;

Beck et al., 2013). In addition, Boyd and De Nicolo (2005) suggest that a more fiercely competitive banking sector could lower market lending rates, thus reducing borrowing costs for entrepreneurs and the default rate of entrepreneurs' investments. Consequently, in the competitive environment brought about by diversification, banks will bear a lower level of credit risk on their traditional loan portfolio, and this will contribute to increaseing stability of the banking sector. Furthermore, as suggested by Boyd and De Nicolo (2005), Schaeck et al. (2009) and Allen et al. (2011), a fiercely competitive environment could help banks to achieve more efficient operation and risks management, which in turn would contribute to the construction of a steady banking system.

However, from the competition-fragility perspective, the more intense competition generated from diversification within the banking industry could make banks less sound. Vives (2011) claims that such a relationship can be explained by the effects through two channels. First, increased interbank competition could increase banks' frangibility by exacerbating the coordination problem between depositors and the bank. Second, increased competition would change the risk-taking behaviour of the banks. In a more competitive environment with more pressures on profits, there would be increased incentive for the bank to take on more excessive risk on either side of the bank's balance sheet, resulting in greater fragility. As suggested by Amidu and Wolfe (2013), this can be assumed as an inverse response; that is, the increased competition generated from a diversification strategy could then stimulate a higher level of diversification, further increasing competition within the banking sector, while at the same time causing the banks to adopt more radical strategies to diversify. Individual banks would thus bear on more insolvency risks, and there would be an increased likelihood of failure.

1.4.10 Business Homogenization and Joint Failure

Barry et al. (2011) suggest that bank managers are likely to choose to diversify the banks' income sources in the expectation that this will separate risk, in order to limit idiosyncratic risk. Hence, managers have incentives to diversify the company beyond the optimal level. However, in doing so they cause harm to the wider financial system, because diversification leads to business homogenization, making institutions more similar to each other and exposing them to same risks, which can lead to joint failure and so are more exposed to the systemic risk (Acharya et al., 2006).

Wagner (2010) proposes a contagion model, which detects the conflicts between bank managers' individual insolvency risk and the systemic risk. The study claims that limited liability incentivizes both bank managers and shareholders to allocate and diversify their portfolio towards correlated assets, and to ignore the risk of joint failures in the banking system brought about by raising bank exposure to common sources of risk. However, such an incentive to managers to over-diversify will in turn harm the wider financial system, because diversification makes institutions more similar to each other, thus exposing them to the same risks and increasing the probability of joint failure (Acharya et al., 2006). Consequently, it creates a fragile financial system, where once a shock or bankruptcy hits an individual bank, the effects would immediately spread and ultimately bring down the whole financial system (Ibragimov et al., 2011). For this reason, diversification might not be conducive to resilience of the banking system, and from a social perspective it might be suboptimal and inefficient (Freixas et al., 2007).

To summarize, there has been extensive research into consolidations in the banking industry. The results suggest that efficient financial institutions should exhibit greater safety and soundness, thus contributing to the stability of the whole financial system. Traditional portfolio theory suggests a specific risk separation effect for banks' income portfolio, and recommends increasing the proportion of non-interest activities. However, from the social perspective, the broadening of financial activities can create systemic crises, as diversification makes institutions more similar to each other, thus exposing them to the same risks, and causing instability in the whole financial market.

1.4.11 Learn-by-Doing Effects

Lee (1996) constructed a learn-by-doing model to investigate the investment and lending decision. According to the model, banks' behaviour and investment portfolio should be improved through the accumulation of information and employee proficiency. That is, in the early stages, poor information could exist in equilibrium with low investment, leading to an underdevelopment trap; however, this trap would be overcome once the banks had accumulated sufficient learning through experience; that is, ‘learning-by-doing’.

Nowadays, the learn-by-doing effects are hardly considered relevant for mature markets, as banks in those markets have already acquired sufficient information and ability to overcome the potential risks and instabilities inherent in non-interest activities. However, given that Chinese banks have only recently received permission to embrace non-interest activities, and are just beginning their diversification process, the learn-by-doing theory still have value for research in the Chinese banking sector. As suggested by Lou (2008), the learn-by-doing effect plays a big role in that market, and leads to the possibility of an inverted U-shaped relationship between diversification and banks’ risk level. By international standards, most Chinese banks are in the early stages of income diversification, where without enough information and professionalism the accumulation of high-leveraged non-interest activities will make those banks less stable. At the same time, some banks may have crossed the diversification threshold and already be enjoying the benefits from diversity. That is, in the early stages of expansion of non-interest activities banks suffer risk-enhancement, but if they continue with the process and pass a certain threshold level, then, assuming that they have gained rich experience and professionalism, and that a sound regulatory system is in place, they can reap a risk discount.

1.5 Endogeneity Problem

More recent studies on the diversification effect in the banking industry place strong emphasis on the two-way relationship between income diversification and banks' other specific characteristics. Such a mutual causality will lead to deterioration of the econometric model, due to the endogeneity bias (Sanya and Wolfe, 2011; Köhler, 2014).

A number of studies have found that high-risk banks are more likely to enter into riskier and high-leveraged non-interest activities, and to propose a more radical diversification strategy (e.g. Lang and Stulz, 1994; Acharya et al., 2006). Similarly, Stiroh (2004) and Agnihotri (2013) state that when facing high volatility of earnings, banks are more likely to expand their businesses scale and to implement merger and acquisition with high-leveraged financial sectors, behaviour that is driven by a risk-taking preference. In addition, with regard to the relationship between performance and diversification, those companies that face constraints upon their business growth and profitability, especially within a highly competitive market, will tend to choose a diversified strategy in order to look for new drivers of profitable growth (Christensen and Montgomery, 1981).

Furthermore, some market-based factors, such as market competition, or government policy, will have influences on banks' diversification level and performance and, simultaneously, on risk indicators. For example, intensive market competition narrows banks' net interest margin, hence greatly shrinks the profitability and performance of the bank's core business, while at the same time it pushes banks to accelerate the process of diversification.

All of the factors mentioned above will lead to a potential endogeneity problem, as will the omitted management strategy variables (Gurbuz et al., 2013) and the sensitivity of bank risk level to macroeconomic shocks (Berger et al., 2000). Therefore, prior studies on the diversification effect in the banking industry have placed important emphasis on this issue (Sanya and Wolfe, 2011; Köhler, 2014). Therefore, in the empirical sections in Chapters 3 and 4, this thesis adopts the generalized method of moments (GMM) model, which is particularly well-suited to overcoming the inconsistency caused by endogeneity.

In detail, in Chapter 3, this thesis employs the system GMM (SYS-GMM) approach introduced by Blundell and Bond (1998). This approach has been widely used in numerous studies to evaluate the diversification-performance relation and to eliminate the endogeneity bias (e.g. Sanya and Wolfe, 2011; Gurbuz et al., 2013; Lee et al., 2014).

In Chapter 4, we argue that, due to the learn-by-doing effect, there could exist a non-linear relationship between bank insolvency risk and the diversification level.

Therefore, we implement the first-differenced GMM threshold dynamic panel estimator approach proposed by Seo and Shin (2016), which addresses the inconsistencies generated by the endogeneity problem. The model provides a non-linear view of dynamic GMM (Bun and Windmeijer, 2010; Hsiao and Zhang, 2015) and allows endogeneity of both regressors and transition variables, which is unlikely to be achieved by employing the standard least squares approach (Seo and Linton, 2007).

1.6 Hypothesis Development

This thesis focuses on the diversification effects on banks' performance, risk and efficiency in the Chinese banking sector. Based on the existing theoretical literature, the thesis tests and explores the following hypotheses:

H1: A shift toward non-interest income will impact profitability and risk-adjusted profitability positively.

Chapter 3 investigates the diversification-performance nexus with a particular reference to profitability and risk-adjusted profitability. Based on the modern portfolio theory and on the resource based view, this study suggests a positive correlation between diversification and performance.

H2: The relationship between income diversification and risk will be positive where there is a low level of diversification, and will become negative where there is a high level of diversification.

Chapter 4 assesses the effect of income diversification on risk. Both empirical and theoretical studies have indicated the existence of a non-linear relationship between diversification and the level of risk. In particular, with the expansion of non-interest activities, accumulated professionalism and a mature supervision system could support the learn-by-doing effects and contribute to eliminating agency and moral hazard problems, thus helping banks gain diversification benefits from risk reduction after they have achieved a certain level of diversification. That is, income diversification makes banks less stable in the early stages of mixed business lines, but they become more stable with the expansion of non-interest income. In this situation, the relationship between diversification and risk can be described by an inverse U-shape.

H3: Diversification levels have a negative correlation with liquidity risk at both low and high levels of diversification, while credit and interest rate risk will be positively correlated with income diversification where there is a lower proportion of non-interest income, and become negatively correlated once the threshold point has been passed.

Given the differences in income structure and in the risk generated from various activities in the Chinese market compared to mature markets, this study also divides the overall risk into different categories, and aims to discover how the diversification level would influence different types of risk. Following Valverde and Fernández (2007), we separate total risk into three categories, namely liquidity risk (LIQUIDITY), credit risk (CREDIT) and interest rate risk (INTEREST). As the off-balance sheet activities cannot be influenced by the capital adequacy ratio, such activities would supply additional liquidity to banks. Therefore, we assume that there should be a negative relationship between liquidity risk and diversification for both low and high levels of diversification. With regard to the credit and interest rate risks, we assume that the relationship between diversification and both risk share the same direction for both low levels of diversification. However, high income diversification can always make banks riskier in terms of credit risk, but less risky for interest risk.

H4: The relationship between income diversification and banks' profit efficiency level will be positive.

In Chapter 5, we investigate the effects of income diversification on both profit and cost efficiency level. According to Rossi et al. (2009), there may exist different and conflicting diversification effects on cost and profit efficiency. With regard to profit efficiency, income diversification could bring about an efficiency premium. As the Chinese banking market is considered to be an oligopolistic mechanism, according to market power theory and the resources based view, diversified business could help banks to access and gain competitive advantages in other financial markets, where they can use their existing resources to support and strengthen the new business.

Moreover, in the Chinese banking sector there is a strong spillover effect between banking and other financial institutions (Luo et al., 2017). Based on the informational advantages theory, business concentration would inevitably lead to information concentration, thereby largely improving banks' overall efficiency level through the construction of an internal capital market and the referral of high-quality customers from the traditional business to more profitable non-interest income business.

H5: The relationship between banks' income diversification and cost efficiency level will be negative, as diversification dampens cost efficiency.

This hypothesis is based on the fact that, in China, banks are subject to strict government intervention and regulatory supervision. Cumbersome government procedures would increase operating costs and the period for the approval of projects, while also serving to alter managers' risk preference from risk neutral to risk averse. The necessity to collect additional high quality loan portfolios to reduce portfolio risks would increase costs, and generally have a negative impact on banks' cost efficiency. Furthermore, the fact that individuals can move between government and bank executive positions increases the agency problem, which in turn can increase banks' monitoring costs and reduce cost efficiency.

H6: Diversification has different effects on banks' performance, risk and efficiency level.

The three sub-groups in the Chinese banking sector, namely G-SIBs, D-SIBs and N-SIBs, differ greatly in terms of scale and business capability. In addition, as mentioned, there exist huge gaps between them in terms of capital restriction, ownership and diversification motivation. These factors create differences in the relationships between income diversification and banks' performance, risk and efficiency level.

1.7 Categorization of the Chinese Banking Market

Since the 2008 global financial crisis, bank capital requirements have been tightened and new resolution regimes enabling the orderly failure of banks are being implemented. Particular attention has been given to systemically important banks. In November 2011, the Basel Committee on Banking Supervision (BCBS) finalized its methodology to identify such systemically important banks and the regulatory approach to reduce the economic impact of their default (BCBS, 2011). To identify the global systemically important banks, the BCBS determined five categories according to the many dimensions of systemic importance: size, interconnectedness, substitutability, complexity and the cross-jurisdictional activity of a bank. This led to the identification of 29 large banks as global systemically important banks (G-SIBs); among these, four are Chinese commercial banks.

Based on the BCBS categorization, in 2014 the China Banking Regulatory Commission (CBRC) announced three categories of banks in China, and implemented different levels of financial restrictions over them. According to the Guidelines for the Disclosure of Global Systemic Importance Indicators of Commercial Banks, commercial banks with total assets below 1.6 trillion Yuan are defined as non-systemically important (N-SIBs), and should have to satisfy only the basic capital requirement ratios, where the tier1 capital ratio and capital adequacy ratio requirements are 5% and 8%, respectively. According these guidelines, there are 27 banks falling into the category of non-systemically important banks.

Commercial banks with total assets over 1.6 trillion Yuan should be defined as systemically important. According to the Guidelines and the list published as a result of Basel III, these can be categorized further as global systemically important banks (G-SIBs) and domestic systemically important banks (D-SIBs). A total of 13 Chinese commercial banks are classified as systemically important.

Furthermore, four of the 13 banks deemed as systemically importance, known as the ‘big four’, are G-SIBs. These G-SIBs, namely the Industrial and Commercial Bank of China (ICBC), Agricultural Bank of China (ABC), Bank of China (BOC) and China Construction Bank (CCB), must possess additional capital that meets or exceeds the uniform requirement of the Basel Committee. According to a China Banking Regulatory Commission Annual Report (2016), owing to the high concentration of the Chinese banking industry, the total assets of these four banks have reached seventy-five billion CNY, accounting for 67.9% of the total assets of the banking industry.

In order to maintain the stability of the domestic banking industry, in January 2014 the China Banking Regulatory Commission (CBRC) issued the Guideline for the Disclosure of the Evaluation Index for D-SIBs. This gave a list of D-SIBs and required qualifying commercial banks to disclose their evaluation index. According to the CBRC, nine national banks fall into the category of D-SIBs. Overall, the capital requirement for systemically important banks is stricter than for N-SIBs. More specifically, D-SIBs must maintain a minimum 8% core tier one capital and 11.5% capital adequacy ratio. For G-SIBs, the China Banking Regulatory Commission further extended the restrictions to require an additional 1% of risk-weighted assets, which should be satisfied by core tier one capital ratio.

In order to test the diversification effect on banks' specific characteristics and stability this thesis adopts all thirteen systemically important banks, both global and domestic, along with twenty-seven non-systemically important banks. Together these forty banks account for 79% of the total assets of the Chinese banking industry.

As explained above, it is necessary to divide the Chinese banking sector according to the categories G-, D-, and N-SIBs. However, the number of banks in each group is relatively small, especially in the G-SIB category, which includes only four institutions. This could lead to bias, and undermine the validity of the estimation results (Blundell and Bond, 1998; Blundell et al., 2001).

The main concern with regard to small sample bias is that the group of G-SIBs, which is which is particularly important for the understanding of Chinese banks' specific characteristics and stability, includes only four banks, and the data for regression covers only 12 years. However, it is useful and valuable to consider this group as an independent category, as reflected in other studies investigating the Chinese banking market, such as Berger et al. (2010a), Chang et al. (2012) and Yin et al. (2013). This is because there exist large differences between G-SIBs and other types of bank in terms of the business scale, total assets and other characteristics. For instance, the Bank of China (BOC), which ranks fourth among the G-SIBs and in the Chinese banking market as a whole, possesses total assets of 3,213 billion USD, and has 311,133 employees. In stark contrast, the Bank of Communications (BOCOM), which ranks first among D-SIBs and fifth in the Chinese banking market, holds total assets of only 1,407 billion USD, less than half that of the BOC, and the number of employees (88,605) is only around a quarter of the numbers employed by the BOC (Bank scope, 2018). Similar differences exist between D- and N-SIBs. For example, all D-SIBs operate nationwide, while all N-SIBs are regional banks. These factors lead to significant differences in the scale of operations, profitability, and the degree of diversity among the three bank groups.

A further point that should be mentioned with regard to the small sample size is that, in the Chinese banking sector, the vast majority of banks are unlisted city and rural banks. The data for these banks are often opaque and undisclosed, while only a small number of banks make available the information required by a study such as this one. As a result, the small sample size problem is prevalent in research in the Chinese banking sector: for example, Zhou and Wang (2008) use 12 commercial banks, while Shen et al. (2010) include 14 banks in their sample.

In the situation of small sample size, the most popular method, OLS, can lead to bias. According to Soto (2009), in this case GMM is more reliable and efficient than OLS, as the GMM estimator is not hindered even when the small sample size means that it is not possible to completely exploit the linear moment conditions. Therefore, in the empirical part of this thesis in Chapters 3 and 4, we adopt GMM estimation in order to strengthen the reliability and efficiency of estimation.

In addition, under the traditional stochastic frontier analysis proposed by Greene (2005) to evaluate banks' efficiency level, the short panel in the Chinese banking market could lead to an incidental parameters problem and affect the accuracy of estimation. Therefore, in the analysis in Chapter 5, we investigate the efficiency implications of banks' income diversification by implementing the stochastic frontier analysis with the within maximum likelihood estimation (WMLE) proposed by Chen et al. (2014), in which the first-difference data transformation eliminates nuisance parameters, thus solving the incidental parameters problem and making the estimation of the efficiency scores unbiased.

Moreover, in order to verify the potential effect generated from the small sample size, rather than separating the sample into three sub-groups and regressing each of them separately, we conduct the robustness tests for the main empirical results by applying dummy variables to the three groups, as shown in the Appendix for Chapters 3 and 5. This alternative analysis allows the retention of more samples and information in the estimation, thus avoiding the small sample size problem. However, in Chapter 4, the threshold model does not allow the addition of an interaction term in both the lower and higher regimes, and it is not possible to get more than one threshold value at the same time. Consequently, there is no robustness test in that chapter.

1.8 Organization of the Thesis

This thesis comprises six chapters. Following this introductory chapter, the rest of the thesis is structured as follows:

Chapter 2 provides a general introduction to the Chinese banking sector and the rise and development of income diversification of Chinese banks. In the chapter, we start off with an introduction of financial reforms and regulatory changes in China, It is then go on to explore the driving forces behind these banks' engagement in non-interest activities and provides an overview of mixed business lines and the incomes thereof by Chinese banks. This is the starting point for analysing business diversification in Chinese banking sector.

Chapter 3 analyses the relation between income diversification and banks' performance. Three sub-groups are investigated with regard to return and profitability to estimate the diversification effects on the performance of different bank groups.

Chapter 4 then explores the diversification-risk nexus in Chinese banks. It tests to uncover the existence of a non-linear relation between banks' idiosyncratic risk, financial distress and diversification level. This chapter also documents that the diversification effect differs among different non-interest activities.

In Chapter 5, we employ advanced stochastic frontier analysis to estimate efficiency score, and dynamic Tobit model with DPF estimator to provide new evidence on whether bank diversification is beneficial to the efficiency score of Chinese systemically and non-systemically important banks.

Chapter 6 provides an overall summary of the thesis. In this final chapter, research findings scattered in earlier chapters are brought together to give an integral picture of the effects of income diversification on Chinese banks. Limitations of the present research and possible avenues for future research are suggested.

Chapter 2

Chapter 2 The Rise and Development of Non-traditional Banking Business in China

This chapter provides the overall picture of the historical process and current status of income diversification in the Chinese banking sector. It begins by outlining the major stages of banking reforms in China. Then, it describes the development of the non-traditional business by Chinese banks. Finally, the driving forces behind Chinese banks' shift to income diversification are discussed.

Chapter 2

The Rise and Development of Non-traditional Banking Business in China

The steady growth of non-traditional business has been an important development of China's banking industry in the recent decades. This takes place amid gradual unfolding of financial reforms in the country including interest rate liberalization, marketization of banking business, and RMB internationalization. Improved banking supervision and financial disintermediation have strengthened the banks' shift to non-traditional activities. In consequence, Chinese commercial banks increasingly look beyond traditional services and to search out new income sources, leading to a shift from a single income structure that relies largely on interest income, to a more diversified income structure. The first chapter has briefly introduced the channels and main composition of income diversification, and given an overall picture of the organization of this thesis. Chapter 2 will describe in detail the major stages of reform of the Chinese banking system, provide an overview of both the historical development and current status of non-interest income, and explain the main causes thereof.

2.1 Introduction

In the recent decades, the Chinese financial sector has experienced rapid growth. By the end of 2017, the country's banking system had become the world's biggest in terms of bank assets. According to China Banking Regulatory Commission, by 2017, the total assets of China's banking institutions reached USD 37 trillion, while the corresponding amount for the Eurozone was USD 31 trillion, and USD 16 trillion for the USA. On top of the rapid growth of bank size, great changes have also taken place in banks' functions, banks' management, and the regulatory system (Laeven and Levine, 2007).

Internationally, it is an established trend that commercial banks, especially large-sized ones, are actively seeking new income streams and no longer depend on interest income alone (Stiroh and Rumble, 2006). In the mature banking markets, the proportion of non-interest income has steadily increased, causing banks to shift their focus away from traditional intermediary functions such as taking deposits, issuing loans, and providing intermediary services, and instead to take on a diversified income structure by providing an extensive range of services.

For China, while the general economy has continued to develop, financial reforms are also well under way, which include interest rate liberalization, RMB internationalization and exchange rate system reform (Deng and Luo, 2014; Liao and

Tapsoba, 2014). Such reforming moves have been accelerating, and placing pressure on banks to pursue a strategy to diversify their income sources. Moreover, improved capital regulation and the financial disintermediation due to rapid development of the stock market in the country have further induced commercial banks to end their reliance on the expansion of loan business as the sole source of their profit growth, cementing the trend for shifting to a more diversified income structure.

Previous studies lack a comprehensive coverage of the development of income diversification in the Chinese banking market. This chapter intends to fill that gap, by providing an overview of the growth of non-traditional banking business in China including a summary of the special nature of the Chinese regulatory framework and explanations for the internal and external reasons that motivate banks to expand their non-interest income.

The Chinese banking industry has undergone profound changes over the past two decades, in terms of changes to the regulatory system, ownership type, market competition and the admission of foreign and private capital. In order to ensure a better understanding of the following chapters it is necessary to have a comprehensive knowledge of this background and development path. Most importantly, during the process of China's banking reform and policy changes, there have been several significant shifts in the income structure of the banking industry. These changes are very helpful to understand the motivations for Chinese banks' diversification, and will be referred to frequently in the subsequent chapters.

The remainder of the chapter is organized as follows. Section 2.2 introduces stages of banking system reforms in China. Section 2.3 analyses the changes to income structure in the mature and Chinese banking markets. Section 2.4 lists several motivations that push banks to adopt a diversification strategy for business expansion, and offers a comprehensive analysis of why they decide to pursue this path. Conclusion is presented in Section 2.5.

2.2 Banking System Reforms in China

Before 1978, China operated an economic and financial system based on central planning principles. The configuration of the economy followed the Soviet command economy model, whereby economic development was regulated by a strict central planning system, including a centralized state banking system (Yao and Wu, 2010). From 1978, the Chinese regulatory authorities implemented several waves of financial reform in the banking sector, with the aim of transforming a policy-driven and monopolistic banking system into a modern and market-oriented one (García-Herrero et al., 2009; Jiang et al., 2013).

The Chinese central bank, the People's Bank of China (PBOC), established in 1949, was the only substantial bank in the Chinese banking system to serve the nation's centrally planned economy (Berger et al., 2009; Zhang et al., 2013). It functioned both as a governmental department implementing decisions made by the State Council, with responsibility for issuing currency and allocating government investment funds, and as a financial institution offering financial services including savings, loans, and the settling of accounts. With over 15000 sub-branches, the PBOC controlled currency in circulation, managed foreign exchange reserves, set the interest rate and took all deposits from, and extended loans to, the public and commercial businesses.

2.2.1 First Stage of Reform: Establishment of a "two-tier" banking system

In 1979 China launched the programme of "reform and opening-up", aiming to satisfy the demand emanating from the more market economic activities emerging from the transition from the centrally planned economy to a market oriented one (Boyreau-Debray and Wei, 2005). As part of the transition, the first reforms in the Chinese banking market were aimed at establishing a "two-tier" banking system (Bonin, 1999). From 1979 to 1984, three specialized banks, i.e. the Bank of China (BOC), Agricultural Bank of China (ABC) and China Construction Bank (CCB) were spanned off from the PBOC or the Ministry of Finance. In addition, another substantial bank, the Industrial and Commercial Bank of China (ICBC), was established. They are to carry out the general functions of commercial banks though still under state controls.

By 1984, these four state-owned banks were well established as commercial banks for different specialities. On top of this, the PBOC was made the central bank of China, performing as the authorities of credit control, currency issuance and monetary policy

(Cai et al., 2019). This separation of the commercial banks and monetary authorities resulted in a "two-tier" banking system which designated the status of PBOC as the central bank and specified the operating rules for other banks under which expansion of credit was constrained by their deposits (Lin and Zhang, 2009). It also established an institutional framework that bestows the central bank a leading role and the big-four state banks form the backbone of the Chinese banking system (He et al., 2017).

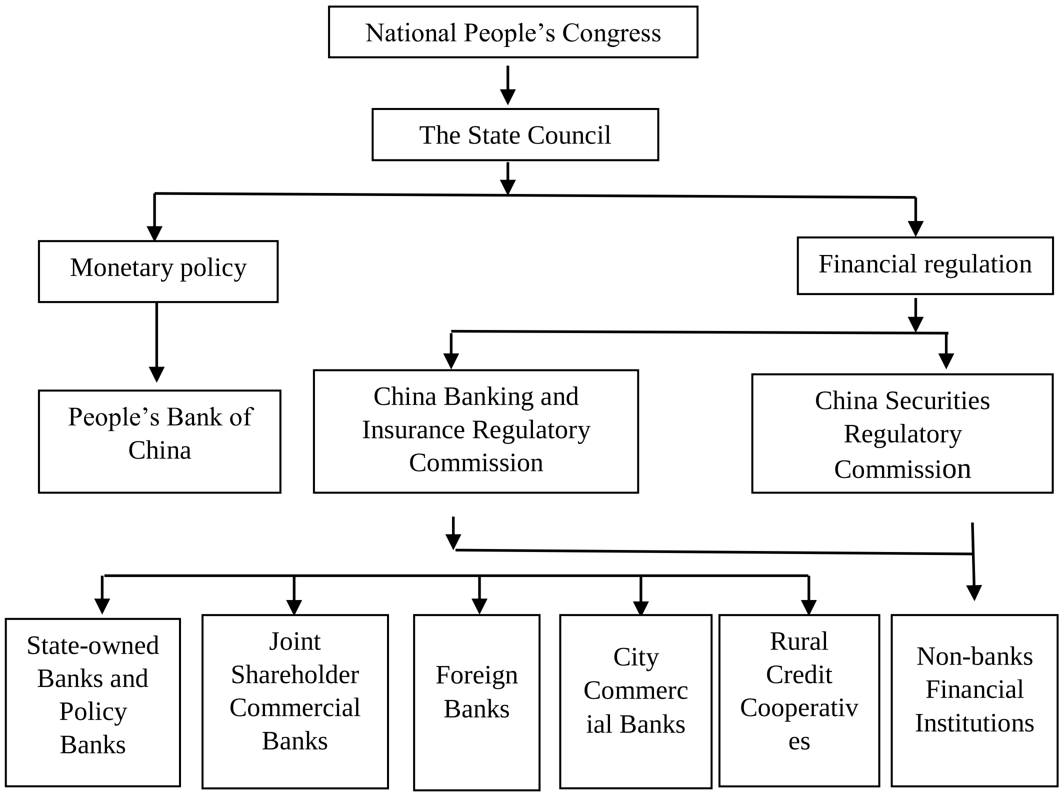
To further promote competition and improve the scope of financial services, by 1992, eight small- and medium-sized shareholding commercial banks were allowed to set up. Of them, six are nationwide banks and two are provincial commercial banks and they offer universal bank services to households and firms, mainly in the cities. At the same time, in addition to a variety of trust and investment companies, many city credit cooperatives were established at both the central and local level. By the end of 1992, 4800 city credit cooperatives with assets of 187.8 billion RMB emerged. These developments were accompanied by a corresponding increase in the total banking assets, from 151.6 billion RMB to 1140.1 billion RMB for the bank sector as a whole, where the share of non-banks in the total bank assets rose from 9.34 to 14.03 percent (Almanac of China's Banking and Finance, 1993).

2.2.2 Second Stage of Reform: Instituting the regulatory framework of "one bank and two commissions"

The second stage of Chinese financial reforms was featured by the intensity of bank supervision. The main aims of the new reforms were to improve banks' ability to manage financial risk, and to create a competitive and modern banking market. The central bank's regulatory roles are re-focused to concentrate on bank supervision, and the two newly established commissions would take over the other regulatory functions.

In 1993, the government started to change the regulatory focuses of the central bank. Between 1993 and 1997 the newly established China Insurance Regulatory Commission (CIRC) and China Securities Regulatory Commission (CSRC) gradually took over some of the PBOC's regulatory functions with regard to the insurance and securities businesses. In 2003, the banking regulatory function was transferred from the central bank to the China Banking Regulatory Commission (CBRC), thereby streamlining and transforming the PBOC into a typical central bank charged with formulating and implementing monetary policy and maintaining the price stability (Zhang et al., 2016).

While the new system has helped reduce excessive concentration of regulatory powers, the rise of non-interest activities in the Chinese banking sector poses new challenges. The expansion of the non-traditional business makes the boundaries among insurance, banking, securities and financing leasing companies gradually blurred. Because commercial banks and their businesses are regulated by both the CIRC and CBRC, the overlapping led to regulatory confusions and inefficiency. In order to improve the regulatory efficacy and reduce costs for, in 2018 the CBRC and CIRC were combined into the China Banking and Insurance Regulatory Commission (CBIRC), a single commission overseeing both sectors, under the direct control of the State Council. The function of drafting relevant laws and regulations for the banking and insurance industries, which was the responsibility assumed by the CIRC and CBRC, has been taken over by the central bank, the PBOC (Wang, 2018). In consequence, these changes led to the emergence of a regulatory framework in China known as “one bank and two commissions”, which is graphed in Figure 2.1.



Source: Author’s creation

Figure 2.1 Financial regulatory framework in China

2.2.3 Third Stage of Reform: Towards a market-oriented economy

Reform after the Asian financial crisis

Alerted by the Asian financial crisis, the Chinese government has taken measures to address the financial risks to the Chinese financial system since the late 1990s and injected substantial amount of capital to stabilise banking market (Jiang et al, 2013). In 1998, the government issued government bonds to the value of 270 billion RMB to provide a capital injection to increase the capital adequacy ratio of state-owned banks. In addition, four financial asset management companies (AMCs) were established, namely China Cinda Asset Management (CCAM), China Orient Asset Management (COAM), China Great Wall Asset Management (CGWAM) and China HuaRong Asset Management corporate (CHAM), each of which belongs to one of the big-four banks. These AMCs are tasked to taking over distressed bank assets, and employing modern techniques in the recovery of those assets. In the year from 1999 to 2000, the AMCs acquired over 1.4 trillion RMB non-performing loans from the big-four banks, while in the year from 2003 to 2004 they acquired another 1 trillion (Wang, 2003). Between 1999 and 2004, the four AMCs also signed debt-to-equity swap agreements with over 1100 state-owned enterprises. In detail, the four asset management companies used funds borrowed from the central bank to buy companies' debt, and then helped the companies to transfer debt to company shares. The funds raised from the sale of those companies' shares to the public could then be used to repay the debt owed to the central bank. These actions alleviated the potential default risk of state-owned banks and stabilized the Chinese financial system to some extent.

Similar to state-owned banks, city credit cooperatives have also accumulated a lot of bad debt and non-performing loans (Hsiao, et al., 2015). As credit cooperatives are under direct control of local governments, the central bank could not effectively influence their assets management and loan decisions. Therefore, in 1995, the State Council issued the Notice Concerning the Creation of City Cooperative Banks, under the terms of which the urban credit cooperatives would be merged into new urban commercial banks, and thus brought into the banking regulatory framework. By the end of 2002, over 2000 urban cooperatives were transformed into 111 city commercial banks (Hamid and Tenev, 2008). They provide financial services to local citizens, while operating under strict financial supervisions by the central bank.

Shareholding system reform

In 2003, the Chinese government started the Shareholding System Reform, which would transform Chinese commercial banks into shareholding corporations (Bin, 2007). This reform was aimed at optimizing banks' ownership structure to improve financial transparency and operational efficiency (Lin and Zhang, 2009; Yao et al., 2008). In early 2004, the State Council utilized foreign exchange reserves to the value of 45 billion USD to inject capital into the COB and CBC for use in financial reorganization and supplementary financing. In 2005, the state-owned Huijin Investment Company injected 15 billion USD into the ICBC. Following further assets restructuring conducted with the assistance of the Minister of Finance, in 2005 the CBC was listed for the first time on the Hong Kong stock exchange (Berger et al., 2009). The following year, the ICBC and BOC were listed on the Shanghai and Hong Kong stock exchanges. Through IPO, state-owned banks could gather funds, increase liquidity and also diversify their ownership (Jia, 2009). To date, a total of 38 Chinese banks have been listed on either the overseas or domestic stock exchanges.

The change to banks' ownership structure brought about by IPO means that banks must be responsible to, and ensure they have enough profit and be better at monitoring the risks management for, their shareholders (Boubakri et al., 2005; Clarke et al., 2005). Thus, it stimulates banks to balance their income structure and increase their income stream. At the same time, income diversification could also diversify banks' portfolios, which could stabilize the income stream and guarantee payments for shareholders.

More importantly, under the shareholding system reform, banks also opened up to strategic investors and foreign capital (Tsai et al., 2014). Several banks, such as the Bank of Beijing, have been officially authorised as foreign capital holding banks. The entry of foreign capital has made the business model and income structure of Chinese commercial banks closer to those of foreign banks, as they become more and more efficient and diversified (Berger et al., 2009; Luo and Yao, 2010; Luo et al., 2017).

In summary, after more than 30 years of gradual financial and banking reforms, China's banking industry has undergone profound development and significantly improved financial stability, efficiency improvement and economic growth (Hasan et al., 2009; Fang and Jiang, 2014; Peng et al., 2014; Wang et al., 2014; Lin et al., 2015), where assets have increased from 304.8 billion RMB in 1978 to 232.25 trillion RMB in 2016. The Chinese banking sector has been transformed from a centrally planned system with one bank that functioned as both policy maker and commercial bank, into a complex two-tier banking system under a regulatory framework with “one bank and two commissions” and with a variety of financial agencies including state-owned banks, private banks, policy banks and other non-bank financial institutions

According to a CBRC annual report, at the end of 2016, China’s banking sector consisted of 3 policy banks, 5 large commercial banks, 12 joint stock commercial banks, 134 city commercial banks, 8 private banks, 1114 rural commercial banks, 40 rural cooperative banks, 1,1125 rural credit cooperatives and 1 postal savings bank. As a result of these developments, combined with the divestiture of policy business from the PBOC and the restructuring of banks’ ownership, the Chinese banking market has been gradually changed from political-oriented to market-oriented, with associated improvements in competitiveness, profitability and diversification level.

2.3 Changes in the Income Structure of China's Banks

2.3.1 Structural Changes in the Mature Banking Market

Diversification is an important trend in the development of the mature banking market. As such, most banks in the mature market can provide customers with a wide range of financial products and services, including banking, securities, insurance, trusts, and other financial categories. Banks in that market have vigorously pursued a mixed businesses strategy and their non-interest business has developed rapidly, becoming a major source of bank revenue, even exceeding traditional interest income. This fast-moving process of diversification has been driven by several factors.

In 1984, the French Banking Act was promulgated, allowing France’s commercial banks to engage in all banking-related financial business and to begin to transition to universal banks. In 1986, the UK authorities announced the Financial Services Act, allowing commercial banks to provide comprehensive financial services including securities and other businesses. The diversification process in the US market began with the Financial Services Modernization Act of 1999, which allowed financial holding companies to operate a variety of financial businesses through the establishment of subsidiaries. The banking markets in Germany and Switzerland have consistently implemented a mixed operation system. The universal banks in those countries operate without any business scope restrictions among financial sectors, and can offer a range of financial services such as commercial and investment banking. The gradual relaxation of financial and businesses regulation in a mixed operation or universal banking system has provided sufficient space for commercial banks to develop their non-interest business and diversify their income streams.

Furthermore, the Basel Accord requirements for capital adequacy has forced commercial banks to increase their liquidity, and at the same time to pay attention to the ratio of assets with different risk-weights. In order to meet the capital adequacy ratio requirements, banks shift from on-balance sheet business to off-balance sheet ones and to allocate to their portfolios more high-yield assets, such as investments, venture capital, securitized products and guarantees (Lozano-Vivas and Pasiouras, 2014). Therefore, the international strengthening of bank capital requirements tends to induce commercial banks to shift in the income structure from interest-based to non-interest-based income.

The rapid development of electronic information technology has also provided favourable technical conditions and a platform for integration of banking and other financial services (Siregar et al., 2017). Technology innovations such as Big Data and Blockchain have made it possible for commercial banks to innovate in financial products and tools, thus facilitating the provision of a more extensive range of financial products and services, the development of e-banking and other online financial platforms, and a consequent expansion of income sources.

2.3.2 Income Diversification in the Chinese Banking Market

The development of non-interest income in the Chinese banking sector has evolved through three stages:

From 1980 to 1992: chaotic development of business diversification

Non-interest income includes revenues from commercial banking, investment banking, insurance, asset management, and financial infrastructure services (clearance, settlement, payments, custody, etc.). In the late 1960s, banks in mature economies started the transition from focusing on traditional lending business to a 'cross-selling' operational pattern. In 1979, trust and leasing business launched in the Bank of China, and become the first type of non-interest business in Chinese market. During the next few years, commissions for stock issuance and consulting businesses also launched. With the further deregulation of the industry, and in particular the United States' Financial Services Modernization Act of 1999, commercial banks are allowed to engage in securities underwriting/brokerage, insurance, and other high-leverage areas such as venture capital. Table 2.1 shows the non-interest activities expansion in the early stage of Chinese banking market.

Table 2.1 Types of non-interest activities in early stage

Non-interest product	Issuance date	Financial institution
Trust business	1979	Bank of China
Business guarantee	1980	China Construction Bank
Agency for foreign currency trading	1982	Bank of China
Forward exchange transaction	1985	Bank of China
Investment advisory services	1987	China Construction Bank
Interest rates and currency swaps	1988	China CITIC Bank
Revolving underwriting facility	1988	Bank of China
Note issuance facility	1988	Bank of China
Forward rate agreement	1988	Bank of China

Source: Author's creation according to China Statistical Yearbook

In 1980, the State Council issued the Interim Rules on Promoting Economic Coalition, which allowed the commercial banks to engage in trust business. Subsequently, Chinese commercial banks also obtained permission to enter the securities and insurance businesses. In 1987, the Bank of Communications became the first bank to engage in the comprehensive management of banking, securities and insurance businesses. During the 1980s, banks were keen to develop universal and multi-functional banks, such that the boundaries between banks and other financial institutions became blurred (Lo et al., 2016). With the rapid expansion of non-interest activities and insufficient regulation, management of non-interest business in China's banking industry were chaotic and the risk management thereof was inadequate.

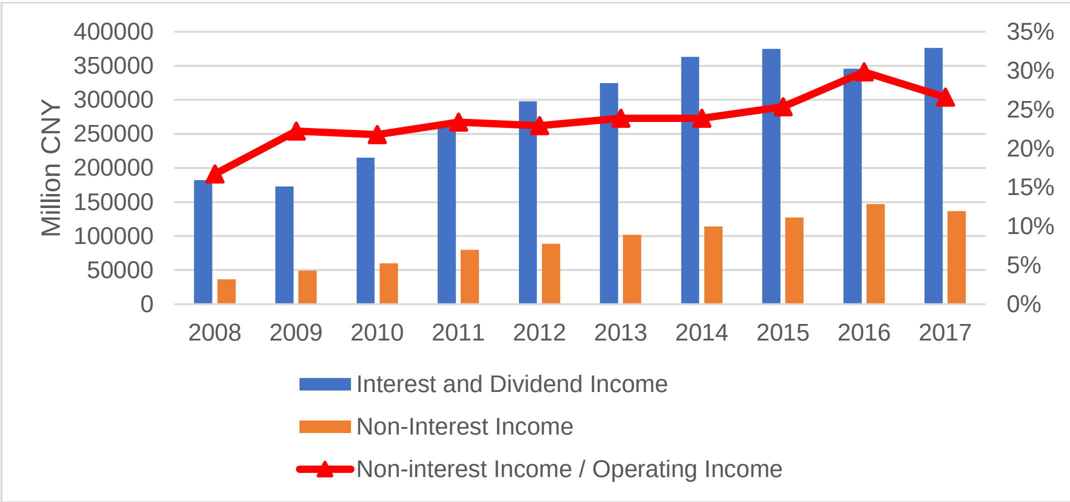
From 1992 to 2000: restricting diversification

Partly to address the problems occurred in the banks' shift to non-interest business, the State Council in 1993 promulgated the Decision on Reform of the Financial System. The document stipulated that commercial banks should be decoupled from the insurance, trust and securities businesses and keep only interest activities in their portfolios. In 1995, the Law of the People's Republic of China on Commercial Banks further forbade merger activities between banks and financial institutions, thus restricting the expansion of non-interest and brokerage business. With increasingly strict restrictions on mixing banks' business lines, the proportion of non-interest income shrank accordingly.

From 2000: gradual reviving of income diversification

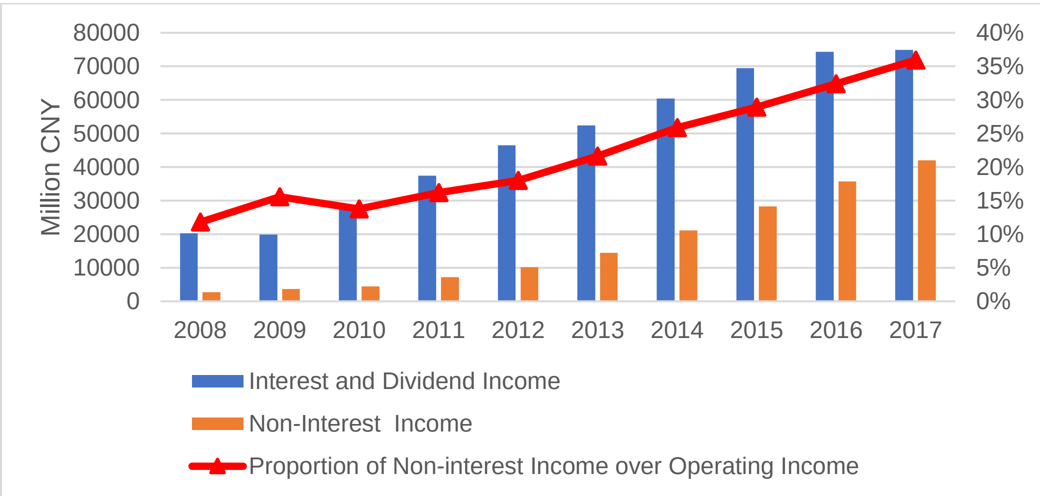
With the gradual establishment of a comprehensive regulatory system, in 2001 the Chinese authorities turned their attention to income diversification in the banking sector. In that year, the PBOC introduced the Provisional Regulations Governing Commercial Banks' Intermediary Business, which expanded the business scope for commercial banks and relaxed restrictions on financial derivatives and agency business, including trading in securities, insurance and government bonds. With this groundwork in place, in 2005 the Chinese financial authorities started a pilot program allowing cooperation among financial institutions, thus increasing the complexity and diversification of banks' income streams. In 2008, the China Banking Regulatory Commission (CBRC) issued the Guidance for Cooperation between the Operations of Banks and Trust Companies, which provided the legal basis to reduce restrictions on bank activity and opened the way for cooperation between non-traditional banking businesses and commercial bank operations. Subsequently, the Securities Regulatory Commission and Insurance Regulatory Commission issued several notices to grant permission for commercial banks to engage in securities and insurance business.

Owing to this expansion of non-interest activities, the total volume of non-interest income of the Chinese banking sector grew from 3.57 trillion CNY in 2006 to 25.40 trillion CNY in 2016, a more than six-fold increase over one decade. However, interest income remains the main source of banks' total income, and non-interest activities occupy only a moderate proportion of overall revenue. More specifically, according to the CBRC, non-interest income accounts for 23.8% of total operating income of the Chinese banking industry (CBRC Annual Report, 2016). Figures 2.2 and 2.3 illustrate the volume and proportion of interest and non-interest income over operating income for the 'Big-Five' state-owned banks, and 12 national joint-stock banks, respectively.



Sources: Author’s creation according to annual reports of the Big-Five banks

Figure 2.2 Volume changes of interest and non-interest income and the growth rate of non-interest income for the Big-Five banks from 2008 to 2017

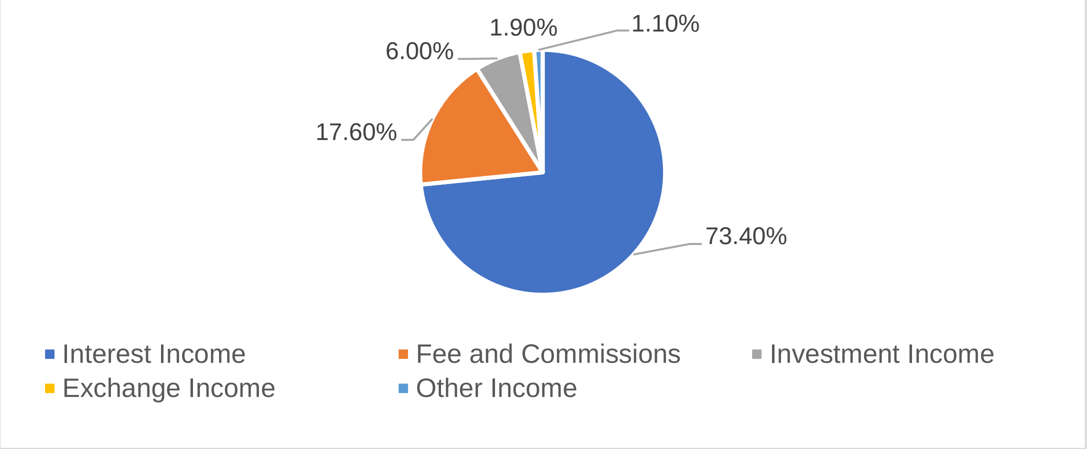


Sources: Author’s creation according to annual reports of 12 joint-stock banks

Figure 2.3 Volume changes of interest and non-interest income and the growth rate of non-interest income for joint-stock banks from 2008 to 2017

We see that, for both banking groups, which together constitute the main body of the Chinese banking sector, the proportion of non-interest income has been rising steadily year by year. In the case of the joint-stock banks, during the early period the amount of non-interest income was relatively small in terms of both volume and proportion. However, over the past decade, joint-stock banks have paid increasing attention to the development of non-interest income. This has led to rapid growth in the average share of non-interest income, which now exceeds that of the Big-Five state-owned banks.

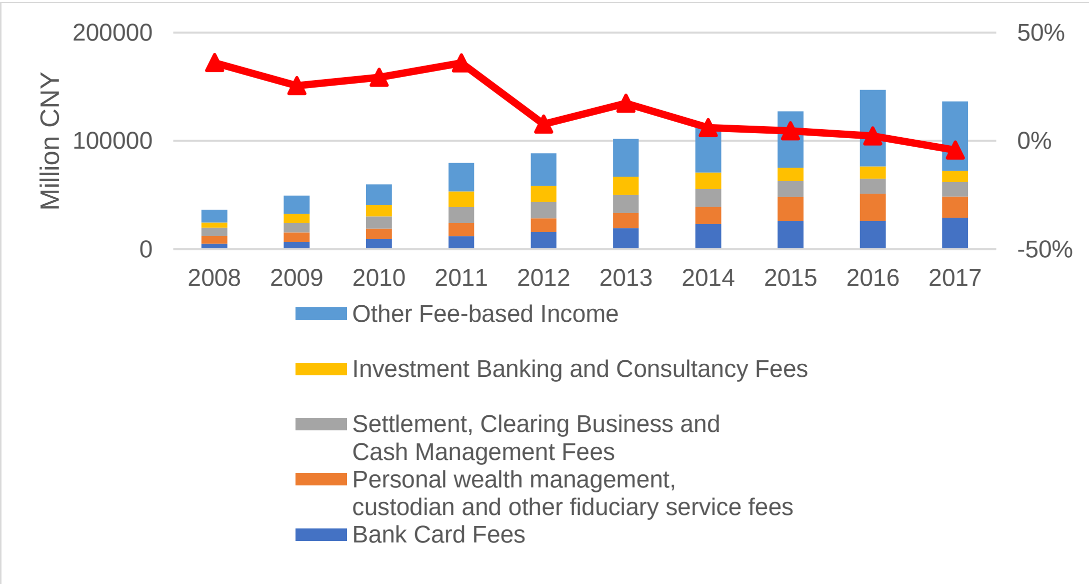
However, to date, the composition of non-interest income is relatively simple, with fees and commissions representing the main sources of non-interest business. As shown in Figure 2.4, according to the CBRC (2016) fee-based income occupies 17.6% of all income in the Chinese banking sector, followed by investment income (6%), exchange income (1.9%) and other income (1.1%).



Source: Author’s creation according to China Banking Regulatory Commission

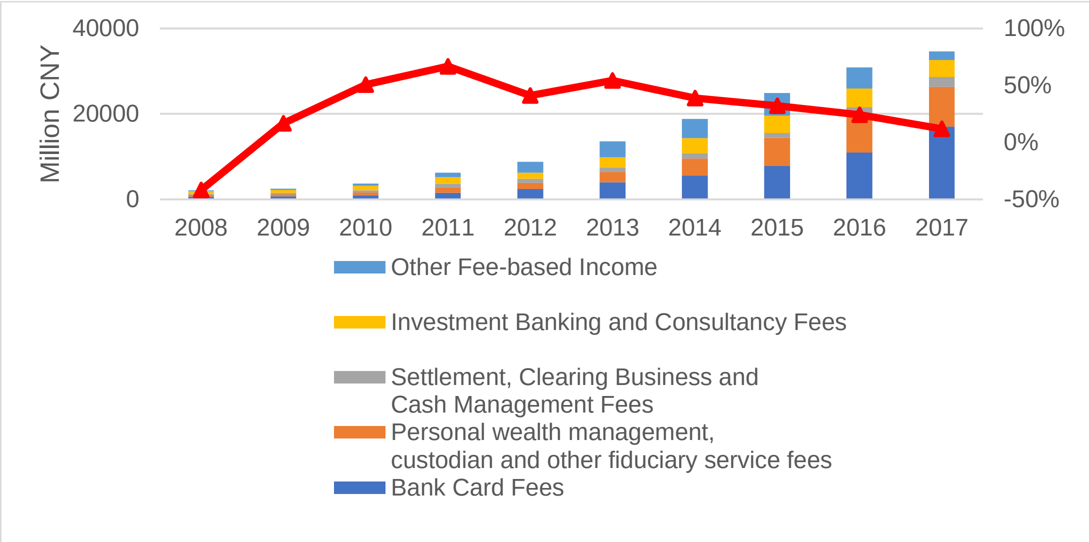
Figure 2.4 The income structure of China's banking industry in 2016

From the above, it can be seen that fees and commissions are the main sources of the non-interest income in the Chinese banking sector. This fee-based income can be roughly divided into six components: bank card fees; personal wealth management fees; custodian and other fiduciary service fees; settlement, clearing business and cash management fees; investment banking and consultancy fees; and other fee-based income. Figures 2.5 and 2.6 show the growth of fee-based income and the volume of each business under fee-based activities, according to figures published in the annual reports of the Big-Five state-owned banks and 12 joint-stock banks, respectively.



Source: Author's creation according to annual reports of Big-Five banks

Figure 2.5 Changes in the growth rate of fee-based income and its components for the Big-Five banks from 2008 to 2017



Source: Author's creation according to annual reports of 12 joint-stock banks

Figure 2.6 Changes in the growth rate of fee-based income and its components for joint-stock banks from 2008 to 2017

We see that, as with overall non-interest income, the volume of fee-based income has undergone a significant increase. Specifically, the fee income of the Big-Five banks increased from approximately 4.63 billion USD in 2008 to 14.65 billion USD in 2017, while for the joint-stock banks, fee-based income increased from 0.4 billion USD in 2008 to 5.24 billion USD in 2017.

However, we also observe that, with the exception of a rapid increase in the amount of fee income for joint-stock banks during the period from 2008 to 2011, the growth rate of fee-based business in the Big-Five and joint-stock banks has fallen into a continuous decline in recent years. Even in 2017, the average growth rate of the Big-Five showed negative growth. This indicates that in China's banking industry, the growth of non-interest income is no longer driven solely by the expansion of fee-based activities. Indeed, especially with the liberalization of the foreign exchange market, in future there will be more and more space for the development of exchange trading and investment.

In addition, from Figures 5 and 6 we can observe the similarities and differences in the composition of fee income for different bank types. First, unlike banks in mature markets, Chinese banks do not value the development of consulting and settlement business; consequently, these two businesses do not occupy a high proportion of the fee-based business in either of the banking groups. In contrast, bank card and personal wealth management account for relatively high proportions of the fee-based business. Further, while the Big-Five banks maintain a relatively balanced mix of business components, the joint-stock banks prefer to earn additional fees and income through the development of bank card business.

From the above it can be seen that there has been a rapid increase in non-interest banking activities, and the proportion of non-interest income in overall operating income is also increasing steadily. Nevertheless, by comparing the figures for the Chinese banking sector with those for mature banking markets, it can be seen that the income diversification process in the Chinese banking sector still lags behind, and there is room for future growth. For example, in 2016 the proportion of non-interest income in the United States banking sector was 32.73%, while the corresponding figure for the European zone was 43.12% (World Bank, 2016).

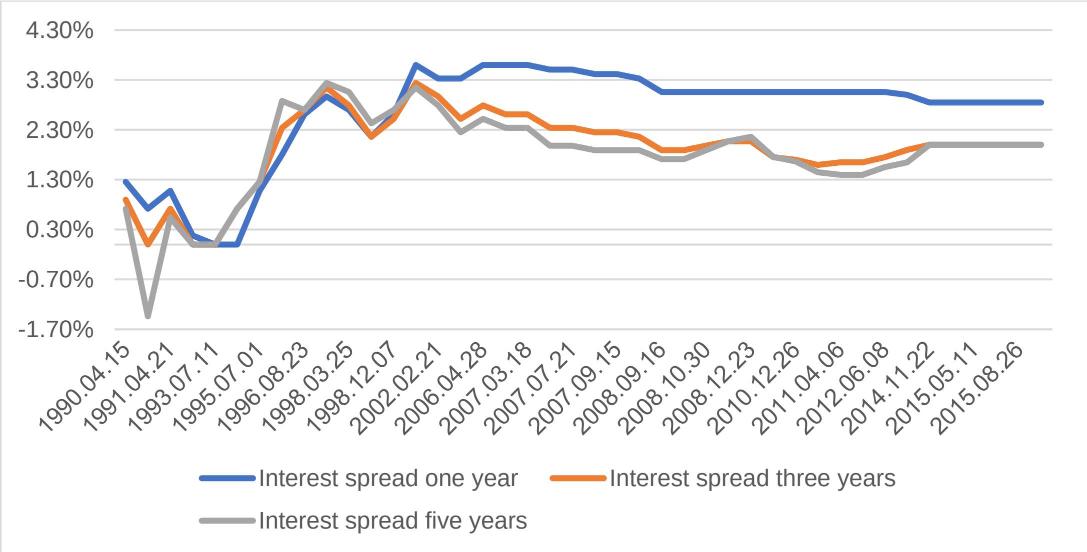
In next section, we highlight the reasons why income diversification has become the subject of much positive attention from bank managers, and why the expansion of non-interest income will be the inevitable choice for the Chinese banking market.

2.4 Motivations for Chinese Banks' Diversification

2.4.1 Constraint-induced Diversification

Market-oriented interest rate reform

For a long time, interest spread in the Chinese banking sector was rather big which contributed to Chinese banks' over-reliant on lending business to earn their revenue and interest income in turn constituted the main avenue for their income stream (Ding et al., 2017). As can be seen from Figure 2.7, the average one-, three-, and five-year benchmark interest spreads over the period from 1990 to 1998 were 1.38%, 1.40%, and 1.34%, respectively. The benchmark interest rate reached its highest level in 1999, and has remained at a relatively high level since then. In order to increase the willingness of the banks to diversify their income stream and promote competitiveness in the banking market, in 2005 the government initiated the market-oriented interest rate reform. The reform was introduced gradually. In 2012, the PBOC allowed Chinese financial institutions the freedom to decide on their own deposit interest rates if it was no greater than 10%. The following year, the PBOC opened up the loan interest rate for financial institutions, which further cut the net interest margin for commercial banks. In 2015 the PBOC removed the ceiling it had imposed on deposit rates and abolished the floor for lending rates (Tan et al., 2016).



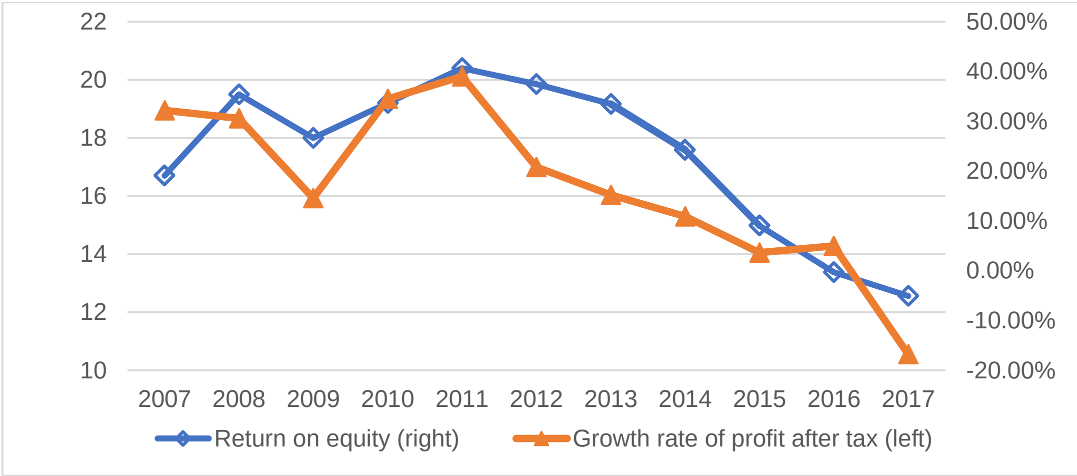
Notes: Interest spread = Benchmark loan rate - Benchmark deposit rate

Source: Author's creation according to the People's Bank of China

Figure 2.7 Benchmark interest spreads in China from 1991 to 2015

The interest rate marketization process leads to functional changes in Chinese commercial banks (Luo, 2017). Interest rate deregulation forces lenders to compete with each other on deposit and loan pricing, which squeezes the net interest margin, or the difference between what lenders pay for deposits and what they collect on loans (Nguyen, 2012; Genay and Podjasek, 2014; Alessandri and Nelson, 2015). As the main source of profit for Chinese commercial banks, the net interest margin falls to record low (Zuo et al., 2014). According to the Bankscope database, the net interest margin for the Chinese banking sector in 2007 was 3.5%, while by the end of 2017 it had decreased to 2.10%. Such a sizable decrease of net interest margin causes significant shrinkage of banks' earnings from lending-based activities and of overall profitability ability (Okazaki, 2017).

The interest rate liberalization has had a large impact on Chinese banks' profitability (Ding, 2017). Figure 2.8 presents the main profitability indexes for banks, namely return on equity (ROE) and the growth rate of profit after tax. Both indicators show a similar trend, where following the fluctuation during the subprime mortgage crisis of 2008 to 2010 in the USA, the profitability of China's banking industry has been in constant decline. In 2017, the level of ROE reached a low of 12.56, and the growth rate of profitability became negative. Therefore, the Chinese banking sector is faced with a significant challenge posed by declining profitability which also claimed by several researches (such as Bikker and Vervliet, 2018). As some non-interest related businesses, such as financial derivatives, securitized products, guarantees and venture capital, can yield high returns, this motivates banks' management to shift to such business leading to adopting the diversification strategies (Elsas et al., 2010; Dietrich and Wanzenried, 2011).



Source: Author's creation according to China Banking Regulatory Commission

Figure 2.8 ROE and profit after tax in the Chinese banking sector from 2007 to 2017

Monetary policy and capital requirements

According to Borio et al. (2017) monetary policy has an important effect on banks' business strategies. Under a loose monetary policy, commercial banks are stimulated to expand their lending businesses, and interest income would dominate their income stream. Conversely, a tight monetary policy would place more restrictions on banks with regard to availability of funds for lending, so income diversification becomes an important alternative for their business opportunity.

After the subprime mortgage crisis and in line with the global tendency, the PBOC adopted a moderately loose monetary policy stance and launched a series of measures to stimulate economic growth by injecting liquidity to the financial market (Yang et al., 2017). This however led to excess liquidity in the financial system and rapid growth of banks' lending. According to CBRC, the total lending volume increased from 27.8 trillion yuan to 42.6 trillion yuan from 2007 to the end of 2009. From 2010, in order to strengthen macro-economic controls, prevent systemic financial risks and avoid increased pace of inflation, the Chinese monetary authorities started to change their monetary policy towards a neutral stance (Xiong, 2012). A gradual raising of the deposit reserve ratio and the interest rate restrained the excessive growth of bank loans and led to a decline in the total amount of bank credit. In 2010, in the wake of the European debt crisis, instability in China's financial market intensified, and the central bank tried to recover excess liquidity in the market by adjusting the excess reserve ratios and open market operations (Jian et al., 2011). In 2012, China's economic growth slowed down, and the PBOC adopted a "prudent and neutral" monetary policy (Zhang and Sun, 2017), thus slowing the expansion of on-balance sheet business and inducing the banks to expand off-balance sheet business.

Coupled with this prudent and neutral monetary policy, the Chinese authorities published a series of regulatory rules and notices, aimed at strengthening bank capital requirements and decreasing banks' overall leverage (Zepeda, 2013). In 2012 the CBRC published the Administrative Measures on the Capital of Commercial Banks (Trial), which set a new minimum level of capital indicators, requiring each bank's core tier one capital ratio, the tier one capital ratio and the capital adequacy ratio to be no lower than 5%, 6% and 8%, respectively. Additionally, commercial banks were required to build up a corresponding capital buffer above their minimum capital requirements and reserve capital requirements, including retained capital and countercyclical capital requirements. For the systemically important banks, they were subject to an additional 1% capital requirement.

In short, regulatory changes in China have resulted in banks seeking other revenue opportunities beyond those from traditional business. New regulations, particularly the capital requirements, affect banks' capital availability as well as its cost. New and stricter capital adequacy regulations mean that banks have to raise more capital to meet the capital adequacy requirements (Zhang et al., 2008). This in turn would force banks to seek new capital or to refrain from expanding their traditional banking business. In addition, new regulatory changes would also increase banks' funding cost, since fewer insider loans would now be available. The risk adjusted capital requirements would also create an incentive for banks to reduce their risk-weighted assets and seek income through non-traditional business (Cohen and Scatigna, 2016). Hence, the capital adequacy rules induce banks to seek income from other sources, mainly from non-interest business, which has lower reserves requirements and hence lower capital cost than are associated with traditional lending. Consequently, banks shift to off-balance activities that can generate non-interest income.

The internationalization of the renminbi

Following the US subprime mortgage crisis, the Chinese authorities accelerated the process of internationalization of the renminbi, in order to bring relief to a monetary system that was too strongly tied to the US dollar (Dobson and Masson, 2009). On one hand, the fluctuation of exchange rates of major international currencies, such as the US dollar, euro, and yen, means that Chinese enterprises face significant exposure to exchange rate risks in their international operations. With increased use of the renminbi in international transaction, the RMB internationalization provides Chinese banks with new opportunities for wider engagement in international business and improved income structure in terms of currency exposure (Cohen, 2012). Potential new RMB businesses such as overseas banking services in RMB deposits and loans, overseas RMB cash management, currency exchange, international bank cards, and account management will result in large fee income.

Moreover, RMB internationalization has the potential of expanding the scale of Chinese banks' international clearing businesses, which will facilitate trade financing and development of financial product chains (Eichengreen and Kawai, 2014). As reported by the annual reports of the Bank of China (2015, 2016), its branches at Hong Kong, Macau and Taiwan have seen a rapid increase in their non-interest income due to the surge in cross-border settlements (see Table 2.2).

Table 2.2 Accounting indicators of Bank of China, 2015 and 2016

	Mainland China		Hong Kong, Macau and Taiwan		Other countries	
	2015	2016	2015	2016	2015	2016
Assets	13,053.1	14,341.7	3,010.9	3,256.5	1,819.8	1,812.5
Liabilities	11,970.9	13,198.4	2,784.0	2,967.6	1,770.8	1,757.5
Operating income	382.3	365.9	75.2	101.7	17.8	19.1
Net interest income	282.1	263.6	31.7	29.3	14.7	13.0
Non-interest income	100.2	102.3	43.5	72.3	3.0	6.1
Fee and commissions	75.2	70.7	14.7	14.4	3.3	4.2
Other non-interest income	24.9	31.6	28.7	57.9	-0.2	1.8

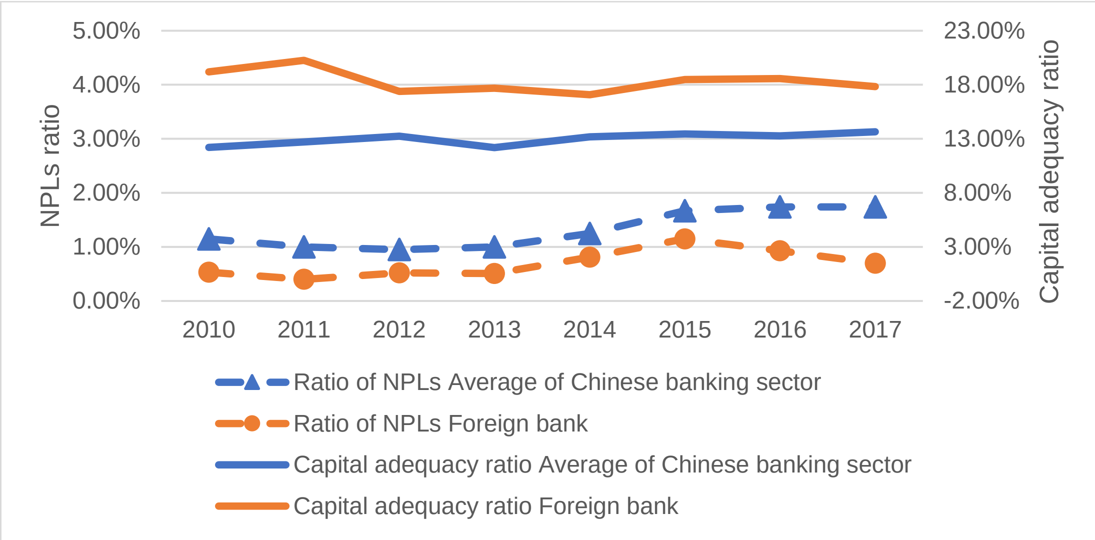
Source: Author's creation according to yearbooks of Bank of China (2015 and 2016)

Reform and opening up in the Chinese banking sector

1. Opening up to foreign capital

Since 2001, China joint the WTO, China has committed to opening up its banking sector to foreign capital and investors. In 2006, in accordance with China's commitment to join the World Trade Organization (WTO), foreign banks was legally granted access to the country's banking industry (Tsai et al., 2014). Under the 2006 Regulations on Administration of Foreign-Funded Banks, foreign banks operating in China are no longer subject to geographical and business restrictions which causing a rapid increase of foreign banks entered into Chinese banking market (Luo et al., 2015).

At the end of 2006, about 30 foreign financial institutions have invested over 19 billion USD into 21 Chinese commercial banks and hold their stakes (Okazaki, 2007). According to the latest National Bureau of Statistics statistics, except for the decrease in total assets of foreign-funded banks in 2015, the total assets of foreign-funded banks have generally maintained a significant upward trend, and the average annual compound growth rate of assets for the 10 years reached 10.57% (National Bureau of Statistics China). By the end of 2016, 37 wholly foreign owned banks had established in China; 68 foreign banks had set up 121 branches, and 145 foreign banks had set up 166 representative offices. The total number of business outlets of foreign banks reached 1031 and their total assets reached 2.93 trillion RMB, tripling the amount in 2007 of 927.9 billion RMB. The entry of foreign banks has promoted competitiveness in the Chinese banking sector and exerted a positive effect on domestic banks' efficiency and their motivations for seeking out new income sources (Claessens et al., 2001; Unite and Sullivan, 2003; Choi and Hasan, 2005). Moreover, the foreign banks also holds better assets quality and better capital solvency ability (see Figure 2.9). Thus the entry of foreign banks also brings advanced risks-management technology to domestic banks and causing positively spillover effect (Lee and Hsieh; 2014).



Source: Author's creation according to China Banking Regulatory Commission and annual report of each foreign banks

Figure 2.9 The NPL ratio and capital adequacy ratio of average Chinese banks and foreign banks from 2010 to 2017

2. Opening up to private capital

Compared with the opening up of the banking market to foreign capital, the easing of restrictions on private capital came relatively late but also increased competition for deposits and putting pressure in Chinese banking market (Hou et al., 2016). In 2005, the State Council promulgated the Several Opinions of the State Council on Encouraging, Supporting and Guiding the Development of Individual, Private and Other Non-public Sectors of the Economy. This allowed non-publicly-owned capital to enter the financial services industry for the first time to stimulate its growth and stability (Milana and Wang, 2013). Specifically, it permitted private capital to enter regional joint-stock commercial banks and cooperative financial institutions. In 2012, the State Council announced a scheme of Encouraging and Guiding the Entry of Private Capitals in the Fields of the Bank Industry. With that, private capital could enter the banking market, which represents an important progress easing the restrictions on the country's state-controlled banking industry. In 2014, the first five private banks gained approval for trial operation (see Table 2.3). These private banks offer financing services specifically to small- and medium-sized enterprises (SMEs), self-employed individuals, and others in special development projects such as the Shanghai and Tianjin Pilot Free Trade Zones. At the end of 2016, the total assets of these five private banks had reached 132.9 billion RMB.

Table 2.3 The first batch of five pilot private banks

Bank names	Main sponsors	Regions	Customer direction	Permission received
Zhejiang E-Commerce Bank	Alibaba Group and Fosun Group	Zhejiang Province	e-bank	26/92014
Shanghai Huarui Bank	JuneYao Group	Shanghai	Enterprises in Shanghai Pilot Free Trade Zone	26/9/2014
WeBank	Tencent Holdings Ltd.	Shenzhen	e-bank	25/72014
Kincheng Bank of Tianjin	Tianjin Huabei Group	Tianjin	Enterprises in Tianjin Pilot Free Trade Zone	25/72014
Wenzhou Minshang Bank	Chint Group	Wenzhou	small-sized enterprises and rural areas	25/72014

Source: Author’s creation according to China Banking Regulatory Commission

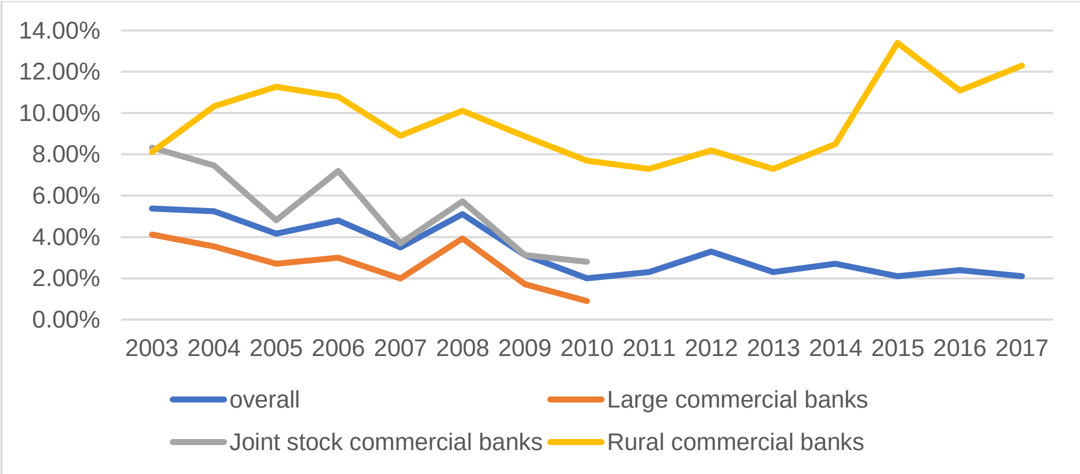
This bodes well for promoting competition in the banking market (Clarke et al., 2005), but it also casts a shadow on the profitability of the major lenders. Such private bank and internet finance can significantly reduce the transaction costs and information asymmetry. Large and medium lenders will probably experience a gradual outflow of depositors if they do not respond to competitive pressure from smaller banks willing to offer higher deposit rates to win retail clients and from innovative Internet financing platforms offered by the likes of Alibaba and Tencent (Wei, 2015).

In summary, a more flexible entry mechanism is pushing the banking sector to launch more financial products in order to compete with private and foreign banks to attract customers and market share. At the same time, it incentivizes banks to diversify their portfolios in order to look for new profit growth opportunity so that they can move away from the traditional model under which the net interest margin was shrinking.

2.4.2 Internal-bank Motivations

Insufficient liquidity due to resource misallocation

Over the last two decades, the total assets of the Chinese banking sector have grown rapidly, increasing over nine-fold from 2003 to 2016 (CBRC, 2017). However, this rapid growth has brought with it the problem of financial frictions and capital misallocation (Lai et al., 2016), where banks put most of their focus on excessive expanding of the loan scale and lavish local branches, thus causing their left with insufficient liquidity.



Source: Author's creation according to the People's Bank of China

Figure 2.10 Excess reserves in the Chinese banking sector from 2003 to 2017[1]

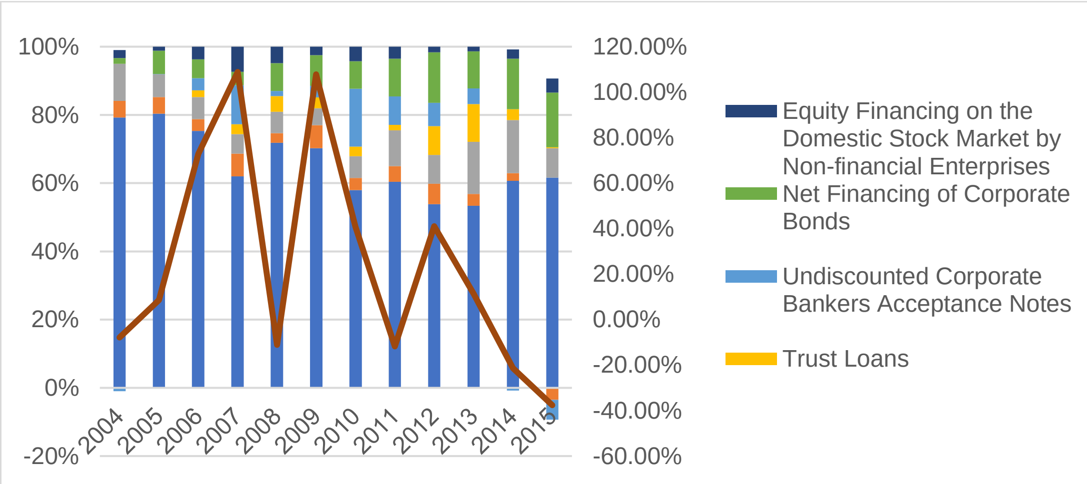
As can be seen from Figure 2.10, the overall level of excess reserves in the Chinese banks shows a downward trend with the exception that rural banks are able to maintain an average ratio of excess reserves over 9%. Lately, with the tempering of the US quantitative easing process, the lack of liquidity issue increasingly becomes a problem for Chinese banks and in response, managers of these banks then engage in more diversification activity to increase non-interest income. This to some extent redresses misallocation of banks' resources and reduce the capital that is taken up by traditional

[1] The People's Bank of China did not report the excess reserves for large and joint stock banks in 2010.

businesses, thus increasing banks' liquidity level. The diversification also provides more financing channels for the banks. Consequently, diversification could help increase banks' short-term capital stocks and make them better able to resist the tightening of liquidity (Pana et al., 2010), thus helping alleviate misallocation of capital and easing banks' financial distress.

Financial Disintermediation

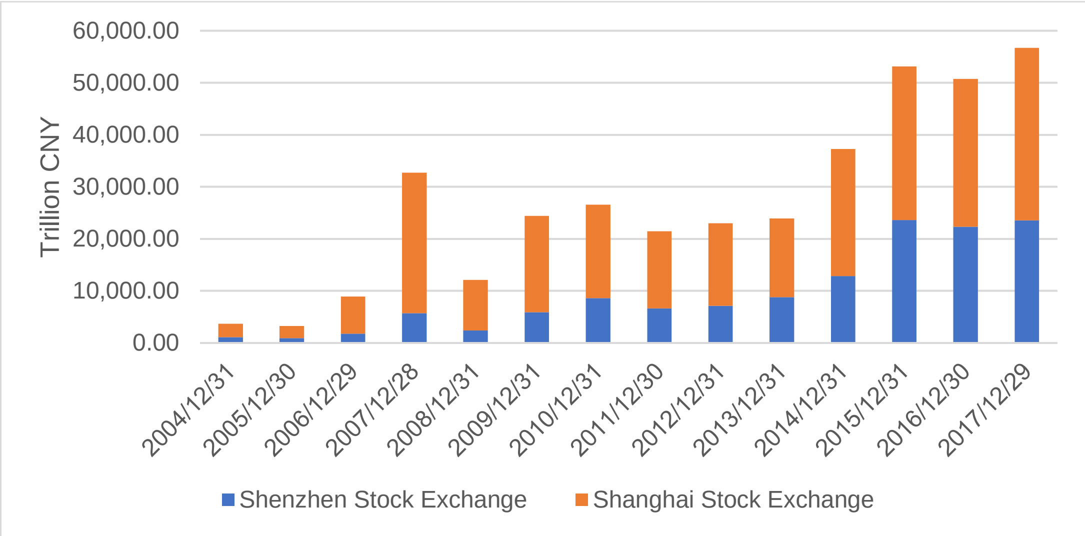
In an increasingly rigorous regulatory environment, banks are faced increased competitions resulting from the squeeze induced by more stringent capital requirements for traditional business (Li et al., 2014). This situation was worsened by the subprime mortgage crisis, which led to banks becoming more prudent in their loan decisions (Jun, 2012). Figure 2.11 presents the growth of non-governmental financing in China, and its structure; it shows the percentages of China's direct and indirect financing in aggregate non-governmental funding. While in 2004 loans accounted for nearly 80% of the total, since then the share has gradually shrunk, reaching its lowest at 51.35% in 2013. During the same period, the growth rate of direct financing reached 108.90% in 2007, and the total volume of direct financing increased nearly seven-fold, from 595.6 billion yuan in 2004 to 4136.9 billion yuan in 2016. The rise of direct financing has significantly eroded the traditional operations that generate interest income and has pushed Chinese banks to diversify their business.



Source: Author's creation according to National Bureau of Statistics of China

Figure 2.11 Growth of non-governmental financing and its structure from 2003 to 2015

Such financial disintermediation is mainly driven by the substantial development of financial markets including that of the stock market, bond market, money market, and gold market, where it creates the opportunity for effective and low-cost financing. The direct financing through financial markets competes with banks' traditional interest-based activities (Perera et al., 2014). In 2004 the combined market value of the Shanghai and Shenzhen stock exchanges was 3705.56 trillion yuan, with the Shenzhen stock market occupying 1104.2 trillion yuan and the Shanghai stock market 2601.43 yuan. At the end of 2017, the combined market value had grown to 56708.6 trillion yuan, an over fifteen-fold increase (see Figure 2.12).



Source: Author's creation according to Shanghai stock exchange and Shenzhen stock exchange

Figure 2.12 Capitalisation of the Chinese stock markets

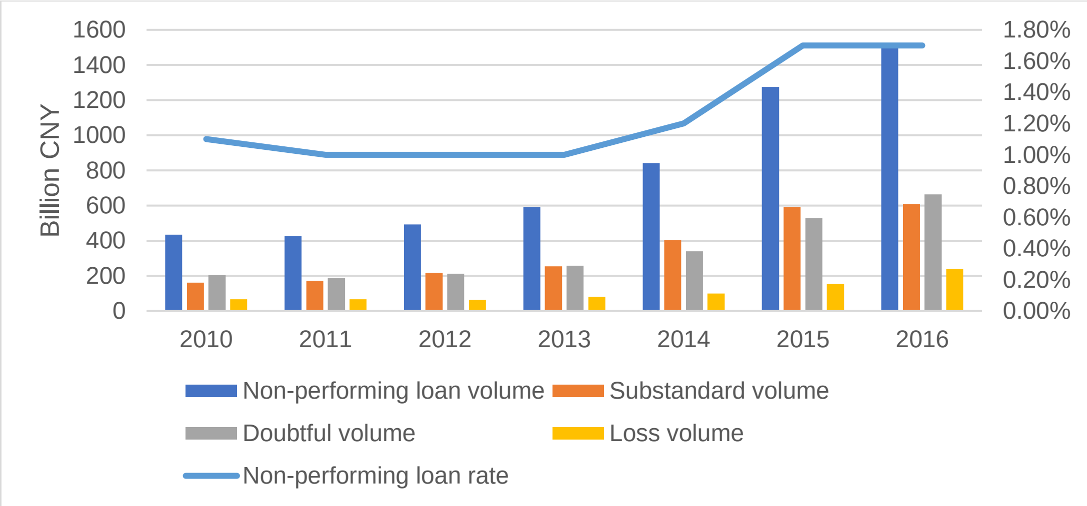
Therefore, Li and Zhang (2013) suggest that the financial disintermediation in turn squeezes the scale of bank lending, and leads to the increases in the pressure on banks' traditional business. Consequently, financial disintermediation and the development of the capital market have promoted the transfer, sale, and securitization of loans and have driven banks to diversify their income stream, change their business modes, and expand their non-interest income. In addition, financial disintermediation promotes product innovation, capital settlement, asset custody, investment banking, and capital market-related businesses, all of which are beneficial to banks that wish to provide diversified investment and financing services for corporate clients.

Non-Performing Assets

In response to the fallout of the global financial crisis, China's top economic planner, the National Development and Reform Committee (NDRC), launched a stimulating programme worth of 586 billion USD, with most of the funds being invested in large-scale infrastructure projects and industrial restructuring (Lee, 2009). Although this eased the impact of the global financial crisis on China, it also raised concerns for the possibility of reckless lending by banks, since the process would be full of government interventions, which would not only distort the efficient allocation of capital but wold also fuel the zealous of the local governments for channelling the funds to the projects in their localities (Chen et al., 2017). This would create the situation in which local governments' finance is over-stretched. In the real economy, it also intensifies manufacturing over-capacity in the industries from shipbuilding to solar energy, threatening occurrence of large numbers of non-performing bank loans (Wang, 2011).

During the recent financial crisis and in the years leading up to it, the Chinese government injected significant amounts of capital into the Chinese banking market in order to write off substantial bad loans and thus create a more healthy level of non-performing loans (NPLs) (Dobson and Kashyap, 2006; Tan and Floros, 2013; Fu et al., 2015). According to the CBRC, the value of NPLs remained stable during the period from 2008 to 2013, fluctuating only slightly within a range from 400 to 500 billion CNY (see Figure 2.13). From 2014, there were signs of a rebound in NPLs, due to the slowdown in the macro-economy. By the end of 2014, the total value of NPLs had reached 842.56 billion CNY, an increase of 348.71 billion CNY on the previous year.

By the end of 2016, the outstanding bad loans had increased to 1.51 trillion yuan, up 19 per cent from a year earlier. As shown in Figure 2.13, the growth rate of non-performing loans increased from -12.81% to 50.72% over the period from 2010 to 2016. The situation prompted the banks to search for new income possibilities, including non-traditional activities.



Source: Author’s creation according to China Banking Regulatory Commissions annual reports

Figure 2.13 Non-performing loans by Chinese banks from 2010 to 2016

2.5 Conclusion

The chapter provides an overview of the rise of non-interest activity in the Chinese banking industry against the background of China’s evolving financial reform and the regulatory changes thereof. Through a process of reform carried out in three waves, the Chinese authorities established a modern banking system. The current Chinese financial system features a framework with “one bank and two commissions”. In which the central bank plays a central role in setting the monetary policy while the main regulatory functions are charged to two regulatory commissions (Zhu and Hu, 2019). Compared to the mature banking market, income diversification by Chinese banks is still at an early stage, and net interest income remains the dominant source of their revenues, occupying 73.4% of the overall Chinese banking income stream (China Banking Regulatory Commission). The proportion of non-interest income in the total revenue of Chinese banks remains relatively low. However, the volume of non-interest income is increasing rapidly (Sun et al., 2017).

Changes in the income structure of China's banking industry are driven mainly by development of financial reforms, deepening financial disintermediation and the process of interest rate marketization (Li and Zhang, 2013). In addition, exchange rate reform and RMB internationalization have provided Chinese banks with new opportunities for wider engagement in international business and improved income structure in terms of currency exposure (Cohen, 2012). China’s opening up to private and foreign capital, and the increasingly stringent regulation on capital requirements, have increased competition for deposits and put pressure on the wider Chinese banking market. Consequently, they have played a significant role in driving Chinese banks to shift from traditional banking to non-interest activity (Borst and Lardy, 2015; Hou et al., 2016).

China’s banks is faced with enormous challenges ahead. The unfolding of financial reforms, tighter bank regulatory rules and economic uncertainties in the world and domestic economy will continue to squeeze bank profits and increase their exposure to risk. In the event, it is imperative that Chinese banks would have to adopt a sound diversification strategy and pursuit mixed business lines to deal with the challenges.

Chapter 3

Chapter 3 Income Diversification and Bank Performance

This chapter investigates the effects of income diversification on the performance of banks in China. By adopting the system-GMM estimation, this research finds the different diversification impacts on performance for three categories of banks. By decomposing non-interest activities into different components, it finds further significant results.

Chapter 3

Income Diversification and Bank Performance

Chapter 2 has described and analysed the major structural reforms undergone by the Chinese banking industry, as well as the dramatic developments in terms of macroeconomics, financial liberalization, capital restriction and internal operational pressures on banks. These have caused huge changes in both the banks' income structure and its components, where non-interest income is increasing in amount and in proportion to banks' assets and operating income. Against this background of structural change, chapter 3 will investigate whether income diversification in Chinese banks results in better earnings and overall performance.

3.1 Introduction

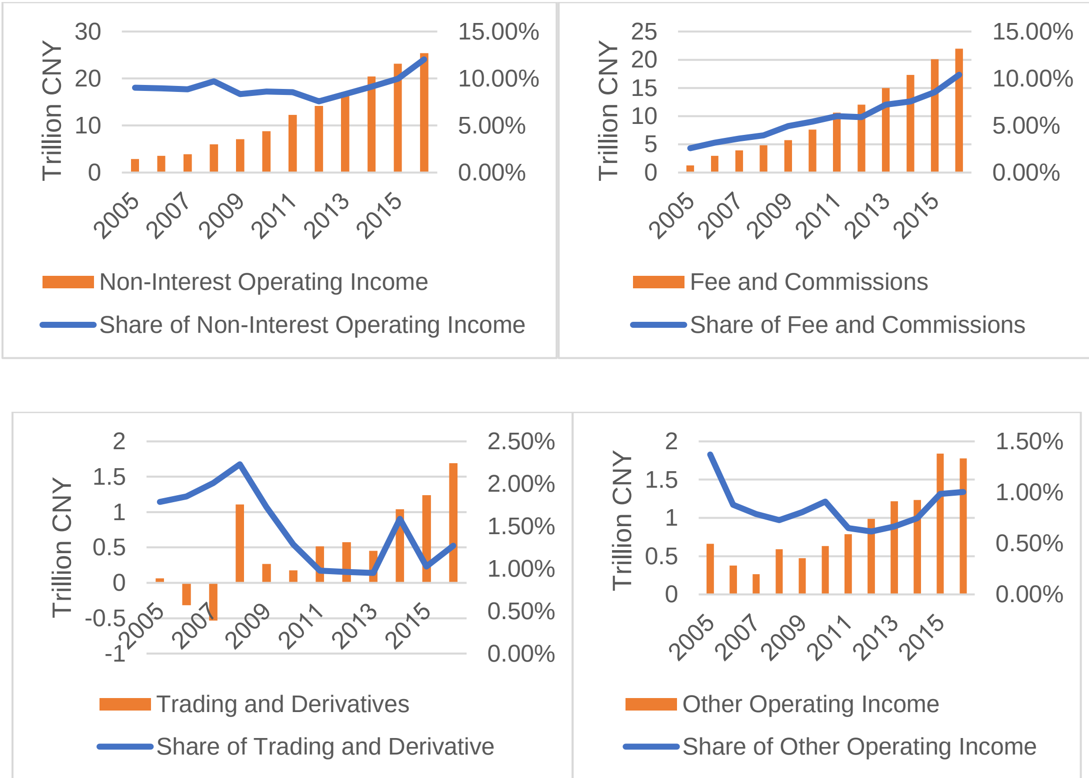
Regulatory changes and banking competition in recent decades have brought about significant changes to the banking market, including the function of financial institutions and their income structure (Allen and Santomero, 2001). In this changing environment, banks are actively seeking new income streams and business lines, as opposed to the more traditional interest margin income (Casu et al., 2016). Hence, there has been a continual increase in banks' non-interest activities, leading banks to diversify from traditional interest-bearing loans to earning income from offering a broad range of mixed financial products and services.

However, evidence regarding the impact of income diversification on bank performance has been inconclusive. Some claim that diversification is beneficial to banks since business expansion to non-interest activities can increase banks' market power and competitive advantages and can offer lower financing cost. On the other hand, there are opposite views that banks with more diversified portfolios are also likely to perform lower well than traditional institutions. Income diversification can also create the presence of too many business lines and disorganized management, offsetting benefits such as supernormal returns and competitiveness. Therefore, whether income diversification can bring a benefit or discount calls for more evidence.

Existing studies have been mostly concerned with mature markets. Only a small though expanding body of the literature has focused on emerging economies. Given their growing importance in international finance, it is desirable to consider how income diversification fares in a wide range of countries, including China. As the China is the largest emerging economy with global importance, studies on China would shed further light on the issue of bank diversification and its consequences.

In the face of the increasingly stringent regulatory capital standards, Chinese banks are under pressure to seek new sources of funding. Meanwhile, market-oriented interest rate reform and financial disintermediation have gradually narrowed banks' net interest margins, encouraging banks to diversify their income stream. Figure 3.1 illustrates the tendency concerning Chinese banks' shares of interest and non-interest incomes in total operating income for 2005 to 2016.

Figure 3.1 shows the amount and share of non-interest income over total operating income, as well as the three underlying activities, including fee-based, trading and other non-interest income. Overall, there is a continually increasing tendency of total non-interest income in the Chinese banking industry; Figure 1 also indicates that the main income source of non-interest income is fee activities, which accounts for 12.04% of total non-interest income, while the share in 2016 was only 2.59 %. Meanwhile, the net operating revenue of trading and other operating income has experienced some fluctuations. Both suffered a decreasing tendency from 2005 to 2007, and then, they dramatically increased in 2008, with the shares then becoming stable from 2008 onward (growing annually by about 0.5% and 0.8%, respectively).



Notes: Operating income = Net interest income + non-interest income

Source: Author's calculations based on BankScope database

Figure 3.1 Chinese banks' non-interest income

This chapter employs a sample of 40 Chinese commercial banks, which accounts for 79% of the total assets of the Chinese banking industry. Following the classification of the China Banking Regulatory Commission (CBRC), this sample is classified into three groups: global systemically important banks (G-SIBs), domestic systemically important banks (D-SIBs), and other banks that are not classified by the authorities as systemically important (N-SIBs). Dynamic panel data models are employed in this chapter to assess banking groups' performance in relation to diversification. The discovered evidence suggests that in the Chinese banking industry, income diversification is generally nonprofitable, but the performance effects vary among G-SIBs, D-SIBs and N-SIBs. G-SIBs exhibit the strongest income diversification benefits, while the performance response of D-SIBs is non-significant. The N-SIBs, however, have a significant diversification discount.

Generally speaking, there are three main factors that undermine the robustness and clarity of previous research in this field. First, many studies refer to a time period before 2005 (e.g. Berger et al., 2010a; Li and Zhang, 2013). However, it was not until 2005 that the Chinese regulatory authorities launched the pilot program allowing cooperation among financial institutions, which increased the complexity and diversification of banks' income streams. In practice, therefore, the process of income diversification by Chinese banks began in 2005, while the non-interest income before that date was mainly from the fee-based business derived from interest income. Moreover, as Lou (2008) points out, before 2005 non-interest income occupied only a very small proportion of operating income, hence the relationship between non-interest income and banks' performance or risk indicators might not have been in evidence, but would be fully generated only from the expansion of interest income. For these reasons, the results of studies that take into account the period before 2005 must be questionable in terms of their accuracy and robustness.

Secondly, most of the existing research in this field uses the pooled OLS estimator, especially in the Chinese case (e.g. Stiroh and Rumble, 2006; Baele et al., 2007; Gamra and Plihon, 2011). However, those studies have noted a potential endogeneity problem, that is, a possible two-way correlation where risky banks might be more likely to expand their diversification to an extreme level and several factors such as business opportunities and competition levels might affect both dependent and independent variables (e.g. Acharya et al., 2006; Stiroh and Rumble, 2006; Baele et al., 2007). Therefore, the use of OLS estimation might allow the introduction of bias, so that it is necessary to control for the endogeneity problems in relation to the diversification process and its conseques. Therefore, this study adopts a dynamic model and compares the results to check whether outcomes differ among several performance indicators. To construct a dynamic model system, GMM (SYS-GMM) for example is used as the econometric model, as it can also solve the endogeneity problem associated with OLS.

Finally, unlike the interest activities, banks' non-interest activities are not subject to capital restrictions. Consequently, in an environment with tight capital restrictions, banks have an incentive to develop non-interest businesses that do not use banks' capital. In other words, the diversification strategy is highly dependent on the capital restrictions. However, this factor is largely neglected by the current literature that seeks to estimate the relationship between Chinese banks' performance and income diversification, which might mean that the results in those studies are subject to bias. To solve this problem, we categorize the banking industry into three groups, i.e. G-SIBs, D-SIBs and N-SIBs, based on the banks' systemic importance.

In more detail, the Chinese banking regulatory authorities impose different capital restrictions on different types of banks, according to the categories of systemic importance. In 2012, China's Banking Regulatory Commission published the Administrative Measures on the Capital of Commercial Banks (Trial), which regulates the minimum levels of the core tier-one capital ratio, the tier-one capital ratio and the capital adequacy ratio for G-SIBs, D-SIBs and N-SIBs. According to this provision, the minimum level of core tier-one capital is set at 5%, and the capital adequacy ratio is set at 8%. D-SIBs are required to have an additional 1% risk-weighted assets, which should be satisfied by the core tier-one capital ratio. However, for G-SIBs, the requirement follows the Basel Committee, which stipulates a minimum 8% core tier-one capital ratio and an 11.5% capital adequacy ratio. Investigation of the diversification effects that takes account of this categorization can offer a new perspective and full consideration of the financial environment and financial restriction in China.

The remainder of the chapter is organized as follows. Section 3.2 reviews the related literature. Section 3.3 presents details of the data sample, variables and methodology. Section 3.4 reports the empirical estimation and results. Finally, Section 3.5 concludes.

3.2 Related Literature

Diversification strategy, originally proposed by Ansoff (1957), is a fluid concept with no fixed definition in the literature. While for some researchers, diversification indicates the horizontal boundaries in terms of products, services and markets (Elsas et al., 2010), others refer to the methods used to achieve the goals of business growth and risk reduction (Hoskisson and Hitt, 1990). In this paper, we define diversification as the process of conglomeration by mixing business lines within an institution. Diversification can be achieved through geographic diversification, international diversification and income diversification (Mulwa et al., 2015). This chapter is mainly concerned with income diversification, which involves the behaviour whereby banks seek new sources and types of revenue other than traditional interest-bearing loans.

Traditional theory arguing for the benefits of diversification is based on the potential that banks may gain benefits through the portfolio effect and economies of scope (Casu et al., 2016). Given that non-interest incomes are not perfectly related to revenues from traditional financial services, diversification can reduce variations in banks' returns and profits. Banks also can benefit from economies of scope since non-interest activities are largely based on the branch infrastructure and electronic banking system; they share the initial cost of their traditional business, leading to increased economic scope and benefiting banks (Jagtiani et al., 1995).

Diversification as a strategy may help banks gain access to market power and release market competition (Barney, 2002). Such competition may in turn bring about efficiency and innovation in the banking industry (Morgan and Samolyk, 2003;

Landskroner et al. 2005; Lepetit et al., 2008). For banks, a diversified business could help them gain competitive advantages in other financial markets and access to market power owing to cheap capital funding. When banks expand their businesses to non-interest activities, they could increase their market power and competitive advantages since the process would offer better investment opportunities and lower financing cost owing to the portfolio effect and economies of scales. Diversified banks can concentrate funds and invest in less competitive markets to control market prices and prevent potential competitors from entering the industry (Palich et al., 2000).

Diversified banks can also obtain rich information from their mixed business lines. The use of the information can help banks overcome information asymmetry when providing traditional lending and improve risk management (Diamond, 1984; Ramakrishnan and Thakor, 1984; Petersen and Rajan, 1995; Stein, 2002; Elsas, 2005; Drake et al., 2009 and Elsas et al., 2010). As banks gain superior informational resources (Massa and Rehman, 2008) and superior technological resources (Miller, 2004) from diversification, the incorporation of such resources would increase their competitive advantage and capability in other financial activities.

However, income diversification might also lead to the presence of too many business lines and to disorganized management, thus creating inefficiency in the internal capital market (De Haas and Van Lelyveld, 2010). Moreover, in a deregulated banking system, especially in the case of emerging market countries, resource allocation could be affected by the agency problem, such that higher profitability projects could not claim advantageous resources. In the long term, such inefficiency and misallocation could harm the interest of banks.

Empirically, early research tends to be based on simulation exercises (e.g., Boyd et al. 1993, Kwan and Laderman 1999, Lown et al. 2000 and Allen and Jagtiani 2000) or on the stock market to determine the effects of diversification (e.g., Lang and Stulz, 1994; Comment and Jarrell 1995 and Baele et al., 2007). Recently, the accounting approach has become the main method that researchers use to identify the effects of diversification on performance. Relying on balance-sheet data, this approach classifies diversification levels by the proportion of non-interest income.

Empirical evidence has been mixed. Landskroner et al. (2005) show that gains from diversification exist. As the scope of banking activities increases, there is a strong positive relation between risk-adjusted performance and asset allocation. Chiorazzo et al. (2008) provide positive evidence suggesting that diversification can improve the trade-off between risk and income for Italian banks. Köhler (2014, 2015) finds that banks' earnings are more stable and profitable if they diversify into non-interest income. Similar results are also reported by Al-Obaidan (2008), Mergaerts and Vander (2016) and Nguyen et al. (2016).

However, further literature indicates it is uncertain whether banks can gain a performance improvement from diversification. Jagtiani et al. (1995) provide empirical evidence from the US banking industry showing that non-interest activities have little or no impact on bank costs. Boyd and Runkle (1993) show that larger and diversified banks employ more financial leverage and earn lower profits. DeYoung and Roland (2001) construct a 'degree of total leverage' framework and find that diversification has a negative impact on performance, which is echoed in Esho et al. (2005). Stiroh (2004) utilizes a sample of consolidated financial holding companies for the period from 1997 to 2004 and finds that an increase in non-interest income does not lead to higher equity returns.

Most of the existing research in the field concerns banks in mature markets. A small but expanding literature has recently emerged to focus on emerging market economies. This body of research generally reports different outcomes than those from mature markets. Khanna and Yafeh (2005) suggest that diversification in emerging market banks leads to only a small discount or premium. Claessens et al. (2001) compare the listed financial groups from the US, Japan and eight East Asian countries, and they find that the level of diversification in East Asian countries is higher and that they maintain a relatively low diversification disadvantage. In their study of seven emerging markets, Lins and Servaes (2002) find a low value discount and further propose that ownership concentration is significantly positively related to the value discount. Sanya and Wolfe (2011) suggest that revenue diversification can also be beneficial to banks in developing countries.

The literature focusing on diversification in Chinese banks is limited because diversification is a fairly recent development in China. As in other markets, results from this limited body of literature are mixed. Studies such as Deng and Li (2006), Chi et al. (2006), Zhou and Wang (2008), and Lou (2008) all find some evidence that diversification may improve banks' performance, but the benefits are often mitigated or even offset by the late development of the move toward diversification and the general lack of skills among bank staff. In the early sample years of these studies (1999 – 2006), Chinese banks were actually highly specialized. It was only in 2005 that the Chinese regulatory authorities started to pilot a program allowing Chinese banks to engage in non-traditional businesses. Thus, in their sample period, non-interest income accounted for only a small proportion of their total income. Meanwhile, at the time, Chinese banks faced a situation in which the proportion of non-interest income was too low to offer significant benefits, while at the same time, less professional management and lacking experience meant that the cost of non-interest activities was high, which reduced net profits（Lou, 2008).

3.3 Variables, Data and Methodology

3.3.1 Variables

All the variables in this research are used at a yearly frequency. The definitions of each variable are as follows:

1). Performance Measurements

Following Berger and Bouwman (2013), we evaluate banks' profitability by using the pre-tax returns on both total assets and equity:

$$ROA_{it} = \quad NIAT_{it}/(\frac{(Asset_{it}+Asset_{it-1})}{2}) \tag{3.1}$$

$$ROE_{it} = NIAT_{it}/(\frac{Equity_{it}+Equity_{it-1}}{2}) \tag{3.2}$$

where ROA_{it}, ROE_{it} and $NIAT_{it}$ refer to return on assets, return on equity and net income after tax for bank i in the period t respectively.

2). Risk-Adjusted Performance Measurements

Following Stiroh (2004) and Sanya and Wolfe (2011), we construct risk-adjusted returns on both assets and equities. They are the ratios of ROA and ROE for a given year to the standard deviation of ROA and ROE over the sample period:

$$RAROA_{it} = ROA_{it}/\sigma ROA_i \tag{3.3}$$

$$RAROE_{it} = ROE_{it}/\sigma ROE_i \tag{3.4}$$

where ROE_{it} and ROA_{it} refer to the pre-tax return on equity and total assets for bank i in the period t respectively. σROE_i and σROA_i refer to the standard deviation of the pre-tax return on equity and on total assets respectively.

3). Income Diversification

The BankScope database divides operating income into interest and non-interest income. Interest income is sourced from the interest on advantages and investment activities, while all other income is classified as non-interest income. Following Stiroh and Rumble (2006), this paper further divides non-interest income into three components: income from trading in foreign exchange and fiduciary activity; fee and commission income from clearing, settlement and other financial services; and other non-interest income.

The most commonly employed measure of diversification in the literature is the Herfindahl-Hirschman Index (HHI). In this measure, income diversification is defined as the sum of the square of proportion of individual income sources over total operating income within a bank as follows:

$$HHI_{i,t} = 1 - \sum_{i=1}^{n}(x_{i,t})^2 \tag{3.5}$$

where n is the number of income categories groups and $x_{i,t}$ measures the category i in period t.. As income can be sourced from interest and non-interest activities, the HHI [2]can be described as:

$$HHI = 1- [(INT / TOR)^2 +(FEE / TOR)^2 + (TRA / TOR)^2 + (OTH/ TOR)^2] \tag{3.6}$$

where INT is gross interest revenue. According to Elsas et al. (2010), the use of INT can avoid distortions caused by the profitability of a bank's interest-based business. However, Bankscope and banks' annual reports do not supply sufficient data on the total income from trading, fees and other activities. As the direct expense for such activities ranges from 5 to 15 percent, we follow Elsas in calculating the net income from such activities. Thus, in the above HHI measure, TOR describes the total operating revenue; COM refers to the ratio of net fee and commission income to total operating income; TRA is the ratio of net trading income to total operating income, and OTH indicates the ratio of net other operating income to total operating income. The HHI ranges from zero (no diversification) to 0.75 (fully diversification). TOR describes the total operating revenue, which is the sum of the absolute values of INT, FEE, TRAD and OTH.

[2] For the sake of consistency, in this thesis the Herfindahl-Hirschman Index is expressed in percentage.

4). Other Variables

NIM: Net interest margin indicates the net interest revenue over total earning assets. This is intended to describe interest-based activity (Lepetit et al., 2008; Busch and Kick, 2009; Köhler, 2014).

LTA: To assess the correlation between diversification and banks' lending business, we use the loans-to-assets ratio (LTA) to measure the level of loan investment at the individual bank level (Stiroh, 2004; Cornett et al., 2010; Calmès and Théoret, 2014).

NON*:* This indicates the ratio of non-interest expenses to total assets. On the one hand, it reflects the efficiency of banks' cost management, where poor cost management is likely to cause lower bank performance. On the other hand, Busch and Kick (2009) maintain that higher investment can improve the monitoring of borrowers and result in better personnel training ability. Thus, it can reduce the potential loss and improve the capacity to expand non-interest activities.

3.3.2 Data Sample

In investigating the impact of income diversification on bank performance, we employ a dynamic panel data model. Yearly panel data are employed, with 40 Chinese banks.

All individual bank-level variables are taken from BankScope and individual banks' own annual reports. The sample period runs from 2005 to 2016. Following the BIS definition and Chinese regulator classification, we divide the sample into three groups, namely, G-SIBs, D-SIBs and N-SIBs, to reflect possible effects of size, managerial efficiency and capital restriction.

The criteria for classification as systemically important banks reflect banks' specific characteristics, which also have a large impact on the effects of banks' diversification. First, banks classed as G-, D-, and N-SIBs are of significantly different sizes. In 2017, G-SIBs possessed average total assets of 3,406 billion USD, while the average assets of D-SIBs and N-SIBs were 808 and 128 billion USD, respectively. Therefore, there are huge gaps between the three groups in terms of business scale. In larger banks the more extensive non-interest business shares the initial cost of traditional business, and non-interest activities can continue to grow as long as they generate fee income. Moreover, as suggested by Gurbuz et al. (2013), large-sized banks generally have better information technology, human capital management and risk management. Therefore, such business expansion could improve the overall productivity and cause technology spillover within the banking system (Canals, 1994; Acharya et al., 2002; Mercieca et al., 2007).

Secondly, in the Chinese banking sector the three groups follow significantly different diversification strategies. For G-SIBs, the diversification process is largely influenced by government intervention. Banks in this category are responsible for piloting

China's financial reform, and lead the industry in terms of the scale and expansion of non-interest activities. In contrast, because D-SIBs operate nationally, and are chiefly concerned with competing with G-SIBs to attract customers and deposits to their interest business lines, banks in this group tend to be less diversified. Meanwhile, the much smaller N-SIBs face capital restrictions and have weak risk-taking capability. Consequently, banks in this group engage in much lower levels of non-interest business than do G-SIBs and D-SIBs.

Thirdly, the three banking categories face different levels of capital regulations. In general, banks in the N-SIBs group must maintain a minimum 8% of the capital adequacy ratio, while for D-SIBs the minimum is 11.5% and G-SIBs are required to hold an additional 1% risk-weighted assets. As suggested by Danila (2013), regulatory restrictions could impact on banks' traditional activities, as they change the banks' risk preference and willingness to fund loans. Specifically, in order to keep deposit resources fully invested and allocated, banks tend to allow a larger proportion of higher-risk credit. Such a policy changes banks' portfolio structure and reduces the quality of assets, making banks and financial systems subject to greater volatility, and causing instability. If managers can originate loans of one default risk efficiently, they will be minimum-cost originators of loans across a spectrum of default risks. This ability to originate loans competitively means that banks will sell the loans for which they possess no comparative advantage in financing. However, such restrictions offer non-interest activities a comparative advantage, as non-interest objectives have a low reserves requirement. Consequently, capital adequacy rules encourage banks to extend their sources of non-interest income. Based on the theory of Flannery (1989) showed that compared with the traditional activities, non-interest activities are less likely to be affected by capital restrictions. Hence the different capital restriction requirements would make banks within the three categories maintain different non-interest expansion strategies and might lead to different results in terms of the diversification effects.

Finally, owing to the differences in the ownership structure, the three banking categories, i.e. G-SIBs D-SIBs and N-SIBs, have different internal governance mechanisms and face varying degrees of government intervention, all of which contribute to creating different diversification effects. For example, all four G-SIBs are state-owned banks, while D-SIBs are national joint-stock banks and N-SIBs are city and rural commercial banks controlled by local governments.

For the reasons stated above, in the following empirical chapters the main sample includes 40 Chinese commercial banks, occupying 79% of total assets of the Chinese banking industry. The banks are divided into three groups: global systemically important banks (G-SIBs), domestic systemically important banks (D-SIBs), and other banks, which are deemed as systemically important (N-SIBs). Drawing from Basel III and the China Banking Regulatory Commission (CBRC), Table 3.1 lists the banks in the sample.

Table 3.1 List of the banks in three categories

No.	Global Systemically Important Banks	Total Assets (million USD)	Number of employees (thousand)
1	Industrial and Commercial Bank of China	4,006,242	453
2	China Construction Bank	3,397,688	353
3	Agricultural Bank of China	3,233,212	487
4	Bank of China	2,989,653	311
	Domestic Systemically Important Banks		
5	Bank of Communications	1,388,023	91
6	Industrial Bank	985,448	62
7	China Merchants Bank	967,141	73
8	Shanghai Pudong Development Bank	942,509	54
9	China Minsheng Bank	906,396	58
10	China CITIC Bank	871,935	57
11	China Everbright Bank	627,840	44
12	Hua Xia Bank	385,301	43
13	Ping An Bank	199,682	14
	Non-Systemically Important Banks		
14	Bank of Beijing	357,793	15
15	China Guangfa Bank	318,342	37
16	Bank of Shanghai	277,623	10
17	China Zheshang Bank	236,002	13
18	Bank of Nanjing	175,251	9
19	Hengfeng Bank	173,893	11
20	Bank of Ningbo	158,493	12
21	Shengjing Bank	158,274	5
22	China Bohai Bank	153,966	7
23	Huishang Bank	139,459	10
24	Chongqing Rural Commercial Bank	139,102	16
25	Bank of Hangzhou	127,978	7
26	Shanghai Rural Commercial Bank	123,174	6
27	Chengdu Rural Commercial Bank	108,355	8
28	Bank of Tianjin	107,794	7
29	Bank of Harbin	86,654	7
30	Bank of Changsha	72,262	6
31	Bank of Guangzhou	67,595	4
32	Bank of Zhengzhou	66,931	4
33	Bank of Chengdu	66,733	6
34	Bank of Chongqing	64,925	4
35	Bank of Dalian	58,659	5
36	Bank of Hebei	51,717	5
37	Bank of Kunlun	48,763	5
38	Bank of Qingdao	47,035	4
39	Guangdong Shunde Rural Commercial bank	45,743	4
40	Bank of Dongguan	40,126	4

Source: Author’s creation according to China Banking Regulatory Commission

3.3.3 Methodology

Existing studies, such as Stiroh and Rumble (2006), Baele et al. (2007), and Gamra and Plihon (2011), widely adopt pooled OLS estimation. Some studies find that income diversification would also impact on banking strategies, and that more risky banks are more likely to diversify (Acharya et al., 2006). In 1995, Berger and Ofek identified a diversification discount without controlling for endogeneity. However, subsequent papers, such as Campa and Kedia (2002) and Villalonga (2004), find that with consideration of the endogeneity problem they get an inverse result; that is, the result becomes positive with the same methodology. More importantly, studies such as Acharya et al. (2006), Stiroh and Rumble (2006) and Baele et al. (2007) also maintain that it is necessary to control for endogeneity, because diversification strategies are correlated with the banks' business opportunities. Furthermore, a number of bank-specific characteristics, such as omitted management strategy variables (Gurbuz et al., 2013) and sensitivity of bank risk level to macroeconomic shocks (Berger et al., 2000), might lead to bias in the estimation and thus increase potential endogeneity concerns (Nisar et al., 2018).

To address this endogeneity problem, Arellano and Bond (1991) propose taking the first difference in order to eliminate the fixed effect and using of difference GMM (DIF-GMM) for the model estimation. However, the proposed DIF-GMM method has the problem of weak instruments (Staiger and Stock, 1994), and it would exacerbate measurement error biases (Griliches and Hausman, 1986). Thus, when the instruments are weakly correlated with the explanatory variables, the DIF-GMM estimation would become close to the OLS-biased estimation.

Developed on the DIF-GMM method, Blundell and Bond (1998) introduce the system GMM (SYS-GMM) approach, which combines both level value and differentiation value in order to reduce potential biases. SYS-GMM adds the exogenous difference of lagged instrument variables to the level equation. Selection of proper instrumental variables can solve the endogeneity problem and allow effective estimation of the panel data. We follow this approach in adopting the two-step robust standard error estimation for the dynamic model.

GMM was originally proposed by Arellano and Bover (1995) and Blundell and Bond (1998). It entails no particular distribution assumptions and the random error terms are allowed to have heteroscedasticity and sequence correlation (Back and Brown, 1993; Harvey and Zhou, 1993). System GMM improves upon difference GMM, which suffered from weak instrument problems, by building a system of two equations - the original equation and the transformed one.

In the first place, a normal dynamic regression model can be written as:

$$y_{i,t} = \alpha y_{i,t-1} + \beta' X_{i,t} + \mu_i + \epsilon_{i,t} \tag{3.7}$$

In this thesis, $y_{i,t}$ refers to the profitability of bank i in the period t. $y_{i,t-1}$ is the lag term for profitability indicator. μ_i is fixed effect and $\epsilon_{i,t}$ is error term. $X_{i,t}$ covers bank's diversification level and other control variables, including the ratios of net interest income to total earning assets, of loans to total assets, and of non-interest expenses to total expenses. Other potential impact factors, such as size, regulatory differences and the extent of moral hazard, as discussed above, can be evaluated over the three sub-groups.

For equation (3.7), the usage of OLS will result in biased and inconsistent estimation because the lagged dependent variable is correlated with the residuals. In order to remove the bias, Holtz-Eakin et al. (1988) and Arellano and Bond (1991) proposed the first-difference transformation of (3.7) as follows:

$$y_{i.t} - y_{i.t-1} = \alpha(y_{i.t-1} - y_{i.t-2}) + \beta'\left(X_{i,t} - X_{i,t-1}\right) + (\epsilon_{i,t} - \epsilon_{i,t-1}) \qquad (3.8)$$

Next, in equation (3.8), the control variables might not be strictly exogenous; rather, they might be related with the new error term, thus introducing potential endogeneity. Arellano and Bond (1991) introduced the lagged levels of the explanatory variables as instruments under the assumptions that the error term, $\epsilon_{i,t}$ is not serially correlated and that the explanatory variables are weakly exogenous. This dynamic panel estimator is referred to as difference GMM, where its moment conditions are:

$$\mathrm{E}\left[y_{i,t-l}\left(\epsilon_{i,t} - \epsilon_{i,t-1}\right)\right] = 0 \ \text{ for } \ \mathrm{l} \geq 2; \mathrm{t} = 3, \dots, \mathrm{T} \qquad (3.9)$$

$$\mathrm{E}\left[X_{i,t-l}\left(\epsilon_{i,t}-\epsilon_{i,t-1}\right)\right]=0 \text{ for } \mathrm{l}\geq 2;\mathrm{t}=3,\dots,\mathrm{T} \quad (3.10)$$

However, as the difference GMM might suffer from the weak instruments problem, especially under the condition of small sample size, system GMM is used to augment the difference estimator by estimating simultaneously in both differences and levels, with the two equations being distinctly instrumented. The additional moment conditions for the regression in level are:

$$\mathrm{E}\left[(y_{i.t-l}-y_{i.t-l-1})(\mu_i+\epsilon_{i,t})\right]=0 \text{ for } \mathrm{l}=1 \quad (3.11)$$

$$\mathrm{E}\left[(X_{i.t-l}-X_{i.t-l-1})(\mu_{i,t}+\epsilon_{i,t})\right]=0 \text{ for } \mathrm{l}=1 \quad (3.12)$$

In order to test the reliability of estimation, this thesis employs two diagnostic tests commonly used with system GMM. First, the Arellano and Bond (1991) test is used to check for autocorrelation in the residuals AR (1) and AR (2). Then, as the effectiveness of SYS-GMM is largely dependent on whether the instrumental variables are exogenous, in order to avoid the over-identifying restrictions (Chiorazzo et al., 2008), this study also uses the Sargan test (Sargan, 1958) to test the joint inspection of instrumental variables. Sargan statistics can be described as $\mathrm{N}^{-1}(\mathrm{Z}'\widehat{\mathrm{E}})(\mathrm{Z}'\mathrm{Z})^{-1}\mathrm{Z}'\widehat{\mathrm{E}}$, which performs as a kind of Wald test, measuring the asymptotic chi-square distribution with degrees of freedom equal to the difference between the number of moments and parameters.

Specifically, in log form the model specification is:

$$PRO_{i,t} = \alpha_o + \beta_1 PRO_{i,t-1} + \beta_2 HHI_{i,t} + \beta_3 NIM_{i,t} + \beta_4 LTA_{i,t} + \beta_5 NON_{i,t} + \varepsilon_{i,t} \tag{3.13}$$

where empirical results of Eq. (3.13) are reported in Table 3.3 and Table 3.4 for whole Chinese banking industry and in Table 3.6, Table 3.8, Table 3.10, Table 3.11, Table 3.12 and Table 3.13 for three Chinese banking groups (G-SIBs, D-SIBs and N-SIBs). Subscript i indicates the i^{th} bank; t is the time period; PRO is profitability (ROA, ROE); the risk-adjusted profitability is represented by RAROA or RAROE; HHI is the Herfindahl-Hirschman Index and the shares of three non-interest components over total income; NIM, LTA and NON are the control variables, namely the ratio of net interest income to total earning assets, the loans to total assets and the ratio of non-interest expenses to total expenses respectively.

3.4 Results

3.4.1 Income Diversification and Performance: Whole sample

Table 3.2 reports the descriptive statistics for our pooled sample. Banks' diversification level is measured by HHI, which ranges from 0.418 to 40.600. The mean value of HHI is 14.690, which is far lower than that of banks from mature markets (Elsas et al., 2010) and other emerging markets (Sanya and Wolfe, 2011). This result indicates that the level of diversification in Chinese banks overall is low and that they have a high concentration of interest earning activities. In addition, bank performance widely varies within the Chinese banking sector. The alternative measures of bank performance, i.e., ROA, ROE, RAROA and RAROE, have a mean value of 0.983, 17.430, 4.196 and 4.228, respectively.

Table 3.2 Descriptive statistics for Chinese banks from 2005 to 2016

Variable definition: HHI: income diversification using Herfindahl-Hirschman Index with the components of interest income and three activities under non-interest income; ROA: return on assets; ROE: return on equities; RAROA: risk-adjusted return on assets; RAROE: risk-adjusted return on equity; NIM: total interest income/total interest expenses; LTA: loans/total assets; NON: non-interest expenses/total assets.

	Mean	Median	SD	Min	Max	Kurtosis	Skewness
HHI	14.690	13.470	7.751	0.418	40.600	3.119	0.677
ROA	0.983	1.050	0.332	-0.201	2.227	3.926	-0.679
ROE	17.430	17.50	6.890	-27.92	41.780	11.780	-1.416
ROROA	4.196	4.023	2.095	-0.509	9.922	2.733	0.376
RAROE	4.228	4.012	2.415	-2.088	14.23	4.367	0.785
NIM	2.769	2.775	0.582	0.701	4.544	3.627	-0.321
LTA	45.950	47.170	9.389	14.380	69.770	3.105	-0.368
NON	0.892	0.909	0.254	0.0330	2.173	4.713	0.187

Table 3.3 reports the results from estimating the dynamic panel models.

Table 3.3 Income diversification and profitability for Chinese banks, 2005 to 2016

This table reports the two-step SYS-GMM dynamic panel estimation results. Our dependent variables are return on assets (ROA), return on equities (ROE), risk-adjusted return on assets (RAROA), and risk-adjusted return on equity (RAROE). HHI indicates income diversification by using the Herfindahl-Hirschman Index with the components of interest income and three activities under non-interest income. NIM indicates total interest income/total interest expenses. LTA is loans/total assets, and NON is the non-interest expenses/total assets. The Sargan test checks the null hypothesis, i.e., that the instruments used are not correlated with the residuals. AR (2) denotes the Arellano-Bond test for the 2nd-order autocorrelation in first differences. Figures in brackets present the standard error. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

	ROA	ROE	RAROA	RAROE
It-1	0.437***	0.529***	0.577***	0.808***
	(0.021)	(0.022)	(0.024)	(0.042)
HHI	-0.002**	-0.102***	-0.047***	-0.019*
	(0.001)	(0.016)	(0.003)	(0.008)
NIM	0.145***	0.069	0.336***	0.083
	(0.004)	(0.227)	(0.080)	(0.047)
LTA	-0.002***	-0.067*	-0.006	-0.007
	(0.001)	(0.027)	(0.006)	(0.008)
NON	0.120***	4.356***	0.587**	0.340
	(0.011)	(0.777)	(0.201)	(0.196)
Constant	0.122*	8.625***	0.253	1.321*
	(2.190)	(7.190)	(1.410)	(2.250)
F-test	0.000	0.000	0.000	0.000
Sargan test	1.000	1.000	0.512	0.999
AR(2)	0.133	0.159	0.900	0.119
Observations	419	415	419	415

Accoridng to Table 3.3, first, evidence from the two-step SYS-GMM regression shows that lagged income diversification (HHI) is positively correlated with present bank performance. This result indicates an accelerator effect from diversification, where past performance has a positive effect on future performance. Next, we find that diversification is negatively associated with profitability (ROA, ROE), indicating a performance decrease from income diversification. To examine the robustness of the result, we also investigate the likely impact on the risk-adjusted performance indicators of both RAROA and RAROE. Overall, for the whole sample, the results show negative effects of diversification on banks' both performance and risk-adjusted performance.

In general, our study echoes the work of Lepetit et al. (2008) and Mercieca et al. (2007), who use mature market data. According to Köhler (2015), the performance discount in mature banking markets mainly originates from over-diversification. However, income diversification in the Chinese banking sector overall is quite low. As suggested by Wagner (2010), a non-linear relationship exists between banks' diversification and performance; at both the lower and the higher levels of diversification, banks are unable to optimize their performance. Hence, it is plausible that the performance decrease for Chinese banks is driven by under-diversification, where non-interest activities incur high initial costs in the early stages of diversification. Given the average low level of income diversification in the Chinese banking sector, banks require several years to absorb these initial costs; hence, we see an overall diversification discount in this market.

In addition, at the stage of low diversification, few managers have appropriate skills to engage in non-interest business. Because non-interest activities have a higher level of relevance among different products than traditional activities, reliance on unskilled staff leads to losses and to a significant reduction in profitability. On the other hand, this implies high initial costs of training specialized workers, which would cause a significant reduction in profitability. Owing to the high level of fixed expenses of non-interest activities, the costs of non-interest income significantly increase and thus net profits become negative, thus causing a reduction in diversification benefits. It is also plausible that the Chinese banking sector is under-regulated. Managers in banks with abundant cash flows would invest in low profit projects, which would increase the moral hazard problem and thus lead to an increase in capital costs (Easley and O'hara, 2004) and inefficient resource allocation (Fisher et al., 2002). Consequently, the value decrease from diversification would be accelerated.

The table also reports several diagnostic test results. The results presented in the last four rows of Table 3.3 show that the F-statistics for all models with four performance indicators are significant. To check for autocorrelation, we use the Arellano-Bond test for autocorrelation serial correlation (AR2). Second-order autocorrelation is statistically nonsignificant. We employ the Sargan test to examine whether our models include effective instruments, and all P-values of the Sargan tests are above the 10% significance level, which indicates that the instruments satisfy the orthogonality conditions required for their employment.

It is conceivable that individual components of non-interest business may perform differently than the overall non-interest activities. To find further evidence for diversification effects across different components of non-interest income, we divide the non-interest income into three categories, namely, fee and commissions, trading, and other income, and the results are reported in Table 3.4.

Table 3.4 Results for three components of non-interest income and bank performance for Chinese banks, 2005 to 2016

This table reports the two-step SYS-GMM dynamic panel estimation results with robust errors. Our dependent variables are return on assets (ROA), return on equities (ROE), risk-adjusted return on assets (RAROA), and risk-adjusted return on equity (RAROE). It-1 refers to the lagged dependent variables by one period. COM is the ratio of net fee and commission incomes to total operating income; TRA is the ratio of net trading income to total operating income; OTH is the ratio of net other operating income to total operating income. NIM indicates total interest income/total interest expenses. LTA is loans/total assets, and NON is the non-interest expenses/total assets. The Sargan test checks the null hypothesis, i.e., that the instruments used are not correlated with the residuals. AR (2) denotes the Arellano-Bond test for the 2nd-order autocorrelation in first differences. Figures in brackets present the standard error. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

	ROA	ROE	RAROA	RAROE	ROA	ROE	RAROA	RAROE	ROA	ROE	RAROA	RAROE
It-1	0.498***	0.523***	0.578***	0.823***	0.461***	0.390***	0.824***	0.705***	0.346***	0.382***	0.618***	1.136***
	(0.028)	(0.023)	(0.019)	(0.037)	(0.019)	(0.014)	(0.013)	(0.013)	(0.023)	(0.028)	(0.040)	(0.028)
COM	-0.005***	-0.180***	-0.074***	-0.037***								
	(0.001)	(0.039)	(0.009)	(0.009)								
TRAD					0.006**	0.105***	0.021**	0.024***				
					(0.002)	(0.027)	(0.007)	(0.003)				
OTH									-0.099***	-0.965***	-0.092*	-0.132***
									(0.008)	(0.278)	(0.042)	(0.023)
NIM	0.131***	0.068	0.386***	0.072	0.173***	0.200	0.128***	-0.070*	0.160***	0.104	0.751***	-0.940***
	(0.007)	(0.182)	(0.095)	(0.070)	(0.010)	(0.207)	(0.038)	(0.030)	(0.009)	(0.262)	(0.086)	(0.224)
LTA	-0.001	-0.057**	-0.004	-0.005	-0.002*	-0.271***	0.006	-0.022***	-0.007***	-0.061***	-0.002	0.016
	(0.001)	(0.018)	(0.007)	(0.007)	(0.001)	(0.024)	(0.003)	(0.006)	(0.001)	(0.014)	(0.007)	(0.009)
NON	0.105***	4.373***	0.540*	0.370	0.121***	13.525***	1.349***	1.887***	0.265***	7.859***	0.754*	2.174***
	(0.010)	(0.615)	(0.239)	(0.212)	(0.018)	(0.732)	(0.052)	(0.146)	(0.038)	(0.559)	(0.293)	(0.531)
Constant	0.138***	8.226***	0.994*	0.669	0.047	10.807***	-0.935***	0.748***	0.427***	7.680***	-0.915**	-0.528
	(0.033)	(1.185)	(0.440)	(0.406)	(0.033)	(1.015)	(0.136)	(0.199)	(0.047)	(0.721)	(0.338)	(0.430)
F-test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sargan test	1.000	1.000	0.394	1.000	0.982	0.740	0.182	0.676	0.780	0.902	0.254	1.000
AR(2)	0.201	0.158	0.957	0.111	0.250	0.253	0.191	0.123	0.143	0.159	0.744	0.144
Observations	419	415	419	415	410	406	410	406	417	413	417	413

As can be seen from the table, the results show that sub-businesses under non-interest activities exert different effects on banks' performance level. Fee and commissions and other activities show a negative effect among our four performance indicators, while trading activities have positive coefficients. This indicates that the diversification discount for the Chinese banking sector is generated mainly from commissions and other non-interest activities, while trading activities would lead to improvements in profitability.

3.4.2 Income Diversification and Performance across Chinese Banking Groups

China's Global Systemically Important Banks (G-SIBs)

Having examined the performance of the Chinese banking sector for the whole sample, we next examine sub-samples of Chinese banks, categorized according to their systemic importance. Table 3.5 below presents summary statistics for the group of China's global systemically important banks. From the table, the mean of the HHI for G-SIBs is 23.560, which is significantly higher than that for the whole sample (14.690). The minimum value of the HHI as a measure for the level of diversification is 11.650, while the maximum is 40.190. Meanwhile, four performance measurements – ROA, ROE, RAROA and RAROE – have a mean value of 1.104, 15.100, 5.705 and 4.532, respectively. The mean of ratio of non-interest income to total assets (NIM) is 2.804%, with a range from 1.049% to 3.626%. The mean loan to assets (LTA) is 50.610%, with a minimum of 42.980% and a maximum value of 58.960%. The mean non-interest expenses over total assets (NON) is 1.002%, with a minimum of 0.628% and a maximum value of 1.396%. There is no significant skewness in the sample. The values of skewness are within the acceptable and expected ranges, indicating that there is no evidence of the data being skewed toward either extreme.

Table 3.5 Descriptive statistics for Chinese G-SIBs, 2005-2016

Variable definition: HHI (%): income diversification using the Herfindahl–Hirschman Index with the components of interest income and three activities under non-interest income; ROA: return on assets; ROE: return on equities; RAROA: risk-adjusted return on assets; RAROE: risk-adjusted return on equity; NIM (%): total interest income/total interest expenses. LTA (%): loans/total assets, NON (%): non-interest expenses/total assets.

	Mean	Median	SD	Min	Max	Kurtosis	Skewness
HHI	23.560	23.570	5.696	11.650	40.190	3.428	0.138
ROA	1.104	1.168	0.301	0.024	1.475	6.836	-1.705
ROE	15.100	17.960	10.660	-27.920	23.430	11.010	-2.891
ROROA	5.705	5.595	2.634	0.063	9.157	1.899	-0.328
RAROE	4.532	6.326	3.736	-2.088	9.422	1.364	-0.062
NIM	2.804	2.845	0.504	1.049	3.626	4.983	-1.032
LTA	50.610	51.090	3.872	42.980	58.96	2.251	0.072
NON	1.002	0.999	0.168	0.628	1.396	2.978	-0.089

Next, Table 3.6 reports the results from estimating the association between the income diversification of G-SIBs and their performance during the period 2005-2016[3]. The results indicate that diversification is an important determinant of banks' performance. From the SYS-GMM estimations, the coefficients of the HHI are significantly and positively associated with all the four performance indicators. The evidence thus shows that diversification has a positive impact on the largest banks in China, i.e., Chinese G-SIBs. This result indicates that Chinese G-SIBs can benefit from diversifying into non-traditional businesses. Consequently, the higher reliance on non-interest income could make G-SIBs more profitable.

The positive results of the performance effect of diversification are significant in that these G-SIBs are of critical importance to the Chinese banking system. The aggregate assets of these G-SIBs account for 49% of the total assets of all Chinese banks, and hence, they are the key player in the construct of China's banking industry. Their success bolsters the stability of the Chinese banking system and also gives a great boost to other banks shifting to non-traditional business.

[3] As the small sample size might result in an incidental parameters problem, this thesis also applies a robustness test by using dummy variables to the catalogue of the three sub-groups. The robustness test results are reported in the Appendix.

Table 3.6 Income diversification and profitability for Chinese G-SIBs, 2005 to 2016

Our dependent variables are return on assets (ROA), return on equities (ROE), risk-adjusted return on assets (RAROA), and risk-adjusted return on equity (RAROE). HHI is income diversification by using the Herfindahl-Hirschman Index with the components of interest income and three activities under non-interest income. NIM is total interest income/total interest expenses. LTA is loans/total assets, and NON is the non-interest expenses/total assets. The Sargan test checks the null hypothesis, i.e., that the instruments used are not correlated with the residuals. AR (2) denotes the Arellano-Bond test for the 2nd-order autocorrelation in first differences. Figures in brackets present the standard error. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

	ROA	ROE	RAROA	RAROE
It-1	0.764***	0.347	0.980***	0.969***
	(0.075)	(0.211)	(0.071)	(0.042)
HHI	0.013***	0.539***	0.082*	0.021*
	(0.003)	(0.105)	(0.041)	(0.010)
NIM	0.0583	5.716***	-0.0686	-0.491**
	(0.031)	(1.646)	(0.175)	(0.162)
LTA	-0.010	-0.441**	-0.093	-0.093*
	(0.009)	(0.160)	(0.053)	(0.041)
NON	0.221***	0.221	1.758**	1.548*
	(0.054)	(1.622)	(0.541)	(0.717)
Constant	0.102	3.975	1.473	4.287*
	(0.270)	(0.420)	(0.450)	(1.980)
F-test	0.000	0.001	0.000	0.000
Sargan test	1.000	1.000	0.998	1.000
AR(2)	0.102	0.260	0.107	0.132
Observations	44	42	43	42

The main source of their success seems to lie in the fact that these big banks are well positioned to exploit the economy of scope resulting from the diversification. As suggested by Gurbuz et al. (2013), large-sized banks generally have better information technology, human capital management and risk management. Therefore, such business expansion could improve the overall productivity and cause technology spillover within the banking system (Canals, 1994; Acharya et al., 2006; Mercieca et al., 2007). In addition, for these established banks, the initial cost incurred from shifting to non-interest business, including building, IT facilities, business reputation and advertisement, can also be largely shared with the traditional business.

The learning-by-doing effect may also have worked for Chinese G-SIBs. Understandably, the initial stages of bank diversification would incur sizable operating losses owing to, say, unexperienced personnel who are unfamiliar with new business lines. However, with expansion of the diversification, such a disadvantage would be offset by the accumulation of more experienced staff or by the learning-by-doing effect (Gamra and Plihon, 2011). With this effect, banking institutions can achieve performance improvement through practice, self-perfection and minor innovations. Consequently, they can progress to reap diversification benefits as long as they have taken care of diversifying according to their specific characteristics, competences and risk levels. It is reasonable to infer that this process may have also occurred with Chinese G-SIBs.

The regulatory difference is another key factor in Chinese G-SIBs' performance gain from diversification. China's Banking Regulatory Commission has implemented different levels of financial restrictions on the three groups, where the lower boundary of the core tier-one capital requirement is higher for G-SIBs than for the other two, at 8%, while the lower boundary for the capital adequacy ratio is 11.5%. Such tight restrictions are an important factor that explains why G-SIBs seek higher levels of diversification. Non-interest activities have the comparative advantage of high reserve requirements. Consequently, the capital adequacy rules act as an incentive for banks to extend their business to earn non-interest income. Further, the stricter capital restriction of banks' activities would also increase banks' effectiveness (Agoraki et al., 2011) and change banks' risk preference (Flannery, 1989). Consequently, a more risk-averse, effective resources-allocation strategy and strict cost management could have led to income diversification benefits in Chinese G-SIBs.

The results of diagnostic tests are reported in the lower panel of Table 3.6. All test results are satisfactory across all model specifications. The P-values of the F tests for the four models are close to zero, indicating the joint significance of our regressors. Regarding the efficiency of the GMM estimation, the results of the Sargan test are nonsignificant; hence, our instruments are appropriately orthogonal to the error. In addition, the coefficient of the AR (2) tests for the second-order serial correlation are nonsignificant at the 1% significance level.

China's Domestic Systemically Important Banks

We now move to examine the performance effect of diversification for China's domestic systemically important banks (D-SIBs). Table 3.7 presents the summary statistics. Compared with G-SIBs, this group has a considerably lower level of diversification: the mean value of the HHI for D-SIBs is 17.230, while the corresponding figure for G-SIBs is 23.560. Regarding the four performance indicators, there is no significant difference between D-SIBs and G-SIBs. The mean value of ROA, ROE, RAROA and RAROE is 0.952, 19.020, 4.208 and 4.976, respectively. Moreover, the mean non-interest expenses over total assets (NON) are lower than those for G-SIBs, implying that the input for non-interest activities by G-SIBs, such as professional training and initial investment, is relatively lower than that of G-SIBs.

Table 3.7 Descriptive statistics for Chinese D-SIBs, 2005 to 2016

Variable definitions: HHI (%): income diversification using the Herfindahl–Hirschman Index with the components of interest income and three activities under non-interest income; ROA: return on assets; ROE: return on equities; RAROA: risk-adjusted return on assets; RAROE: risk-adjusted return on equity; NIM (%): total interest income/total interest expenses. LTA (%): loans/total assets, NON (%): non-interest expenses/total assets.

	Mean	Median	SD	Min	Max	Kurtosis	Skewness
HHI	17.230	15.610	7.977	4.789	40.600	2.685	0.555
ROA	0.952	0.999	0.280	0.133	1.460	3.128	-0.673
ROE	19.020	18.380	5.245	4.176	41.130	6.018	0.837
ROROA	4.208	4.263	1.602	0.431	7.925	2.732	0.107
RAROE	4.976	5.171	1.707	0.586	8.038	2.424	-0.285
NIM	2.764	2.797	0.387	1.733	3.847	3.192	-0.336
LTA	51.950	51.690	6.958	33.580	67.360	3.225	-0.091
NON	0.951	0.959	0.194	0.502	1.439	2.860	-0.168

To ensure the robustness, we estimate two different kinds of models, one for profitability (ROA, ROE) and the other for risk-adjusted performance (RAROA, RAROE), using the two-step SYS-GMM estimator with robust standard errors procedures. The results for D-SIBs are displayed in Table 3.8. Similar to the case of G-SIBs, the HHI index of D-SIBs is positively correlated with both sets of performance indicators. D-SIBs can gain a performance improvement from income diversification. However, compared with those for G-SIBs, the coefficients for D-SIBs are relatively small, and all are nonsignificant. The results may be explained by the fact that banks in this group have a smaller size than the G-SIBs, and hence, the improvement from economy of scope might not be sufficiently large to offset the performance. For these relatively small banks, the high initial diversification cost and staff's lack of experience might lead to them showing no significant performance gains from diversification.

We also report the diagnostic test results. The F-test yields a significant P-value at the 5% level, indicating that variables in the models are not jointly nonsignificant. Regarding the efficiency of GMM estimation, as all coefficients of the AR (2) and the Sargan tests are nonsignificant, we can conclude that the instruments used are not correlated with the residuals, and there is no problem of autocorrelation. Thus, the models are reasonable and statistically acceptable.

Table 3.8 Income diversification and profitability for Chinese D-SIBs, 2005 to 2016

Our dependent variables are return on assets (ROA), return on equities (ROE), risk-adjusted return on assets (RAROA), and risk-adjusted return on equity (RAROE). HHI is income diversification by using the Herfindahl-Hirschman Index with the components of interest income and three activities under non-interest income. NIM is total interest income/total interest expenses. LTA is loans/total assets, and NON is the non-interest expenses/total assets. The Sargan test checks the null hypothesis, i.e., that the instruments used are not correlated with the residuals. AR (2) denotes the Arellano-Bond test for the 2nd-order autocorrelation in first differences. Figures in brackets present the standard error. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

	ROA	ROE	RAROA	RAROE
It-1	0.523***	0.999	0.646***	0.743***
	(0.056)	(1.225)	(0.088)	(0.082)
HHI	0.001	0.002	0.039	0.065
	(0.002)	(0.677)	(0.033)	(0.046)
NIM	0.249*	-1.548	0.110	-1.008
	(0.090)	(8.686)	(0.532)	(0.781)
LTA	-0.003	0.266	0.089	0.150*
	(0.002)	(1.017)	(0.050)	(0.074)
NON	0.003	2.075	2.112	3.636
	(0.115)	(18.300)	(1.245)	(1.870)
Constant	-0.083	-11.560	-5.894	-8.214
	(-0.320)	(-0.160)	(-1.520)	(-1.460)
F-test	0.000	0.000	0.000	0.000
Sargan test	0.495	1.000	0.992	0.327
AR(2)	0.573	0.434	0.568	0.172
Observations	99	97	97	97

Other Chinese Banks (N-SIBs)

Table 3.9 reports the summary statistics for other Chinese banks (N-SIBs). Compared with banks in the G-SIBs and D-SIBs groups, N-SIBs have the lowest mean of diversification, at 12.390, which is much lower than that of the G-SIBs (23.560). Interestingly, compared with G-SIBs and D-SIBs, N-SIBs have a similar level of mean profitability (ROA, ROE). However, concerning risk-adjusted performance, both RAROA and RAROE variables are significantly lower for N-SIBs than for the other two groups. This result implies that Chinese N-SIBs have poor risk management. In addition to banks' income diversification, we control for several other characteristics that might affect bank performance. The mean net interest margin (NIM) is 2.765%, with a minimum of 0.701% and a maximum value of 4.544%. The mean loan to assets (LTA) is 43.090%, with a minimum of 14.380% and a maximum value of 69.770%. Meanwhile, N-SIBs have the lowest ratio of non-interest expenses to total assets (NON), at 0.854% compared with 1.002% for G-SIBs and 0.951% for D-SIBs. This result indicates that staff training costs and potential losses from non-professional operation are lower for N-SIBs, leading to a higher probability of operational loss.

Table 3.9 Descriptive statistics for Chinese N-SIBs, 2005 to 2016

Variable definitions: HHI (%): income diversification using the Herfindahl–Hirschman Index with the components of interest income and three activities under non-interest income; ROA: return on assets; ROE: return on equities; RAROA: risk-adjusted return on assets; RAROE: risk-adjusted return on equity; and NIM (%): total interest income/total interest expenses. LTA (%): loans/total assets, NON (%): non-interest expenses/total assets.

	Mean	Median	SD	Min	Max	Kurtosis	Skewness
HHI	12.390	11.940	6.591	0.418	37.760	4.416	0.926
ROA	0.975	1.040	0.350	-0.201	2.227	3.833	-0.587
ROE	17.240	17.03	6.550	-15.700	41.780	6.105	-0.399
ROROA	3.955	3.843	2.060	-0.509	9.922	2.863	0.418
RAROE	3.921	3.639	2.312	-1.452	14.230	6.783	1.475
NIM	2.765	2.752	0.649	0.701	4.544	3.158	-0.247
LTA	43.090	42.960	9.468	14.38	69.770	2.991	-0.107
NON	0.854	0.867	0.275	0.033	2.173	4.966	0.471

Then, in Table 3.10, we report the regression results for the effect of diversification on four bank performance variables when adopting the two-step SYS-GMM dynamic panel model. We can see that for N-SIBs, shifting from traditional banking towards non-interest activities significantly reduces their performance in terms of both profitability and risk-adjusted profitability, which means that for banks with low levels, diversification into non-traditional income will adversely affect their returns and risk.

Table 3.10 Income diversification and profitability for Chinese N-SIBs, 2005 to 2016

Our dependent variables are return on assets (ROA), return on equities (ROE), risk-adjusted return on assets (RAROA), and risk-adjusted return on equity (RAROE). HHI is income diversification by using the Herfindahl-Hirschman Index with the components of interest income and three activities under non-interest income. NIM indicates total interest income/total interest expenses. LTA is loans/total assets, and NON is the non-interest expenses/total assets. The Sargan test checks the null hypothesis, i.e., that the instruments used are not correlated with the residuals. AR (2) denotes the Arellano-Bond test for the 2nd-order autocorrelation in first differences. Figures in brackets present the standard error. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

	ROA	ROE	RAROA	RAROE
It-1	0.465***	0.612***	0.657***	0.939***
	(0.032)	(0.048)	(0.085)	(0.025)
HHI	-0.003***	-0.131***	-0.022***	-0.037***
	(0.001)	(0.027)	(0.007)	(0.010)
NIM	0.141***	0.0363	-0.131	-0.0981
	(0.023)	(0.301)	(0.110)	(0.082)
LTA	-0.002	-0.088**	-0.025	-0.006
	(0.002)	(0.032)	(0.014)	(0.007)
NON	0.063	3.745**	1.786**	0.528*
	(0.042)	(1.285)	(0.561)	(0.247)
Constant	0.366***	11.510***	1.148	0.476
	(5.310)	(6.940)	(1.740)	(0.800)
F-test	0.000***	0.000***	0.000***	0.000***
Sargan test	1.000	1.000	0.999	1.000
AR(2)	0.161	0.567	0.838	0.813
Observations	276	276	276	276

For Chinese N-SIBs, non-interest income has consistently accounted for only a small proportion of their total operational income. Positive impacts of diversification into non-interest activities on their profitability, if any, could hardly be sizable. Rather, owing to the necessary expenses, the cost of non-interest income could be higher than the possible gains, turning net performance into negative. Moreover, with a low level of diversification, these banks could hardly benefit from the learning-by-doing effect; instead, they lack a sufficient number of experienced workers to improve the rationality of operating decisions, which negatively affects their performance.

These N-SIBs also suffer from financial deregulation. Compared with G-SIBs and D-SIBs, N-SIBs operate under lower financial restrictions. Consequently, managers have less incentive to seek better business opportunities through financial innovation, which would in turn diminish banks' performance owing to problems such as moral hazard. Agoraki et al. (2011) maintain that a more relaxed capital restriction would reduce banks' effectiveness. Consequently, an ineffective and less risk-averse resource allocation strategy and cost management under financial deregulation could lead to an income diversification discount.

Size also matters here. The majority of Chinese N-SIBs are small-sized banks. Furthermore, they invest far fewer resources in new business lines. As shown in Table 3.8, the ratios of NON are rather diverse among G-SIBs, D-SIBs and N-SIBs. While the average NON for the Chinese banking sector as a whole is 0.892, G-SIBs have the highest mean value (1.002), followed by D-SIBs (0.951) and N-SIBs scores (with only 0.854). Thus, N-SIBs invest fewer resources into non-interest activities. As they lack efficient resources for shifting to new financial products and the relevant experience needed to manage the new product mix, it is difficult for these small banks to exploit economies of scope since they have limited technical capacity and since they cannot provide a lower marginal cost for their financial product in order to offset the increase in fixed costs or inefficient risk controls (Mercieca et al., 2007).

The last three rows in Table 3.10 present the diagnostic test results for the models. All models pass the F tests, and their construction is acceptable, with all variables not jointly nonsignificant. The results for both the AR (2) and Sargan tests are nonsignificant for all models, suggesting that we can conclude that the instruments used in the GMM models are reasonable and statistically acceptable.

3.4.3 Effects of Diversification on Performance by Components of Non-interest Activities

Following the arrangement of the previous section, we have also subdivided the non-interest income into three categories, and then studied whether the three types of diversification have different effects on different bank groups. The results presented in Table 3.11 indicate that the fee-based activities have different effects for G-SIBs than for the banking sector as a whole; that is, there is a significant and positive effect on the performance of G-SIBs, rather than a diversification discount. Turning to trading activities, we suggest that this business line will also improve bank performance among G-SIBs. The only negative effect for banks in this group is generated from other activities, which can be explained by the high leverage nature of those activities, and by a lack of skilled workers.

Table 3.11 Results for three components of non-interest income and bank performance for G-SIBs, 2005 to 2016

This table reports the two-step SYS-GMM dynamic panel estimation results with robust errors. Our dependent variables are return on assets (ROA), return on equities (ROE), risk-adjusted return on assets (RAROA), and risk-adjusted return on equity (RAROE). It-1 refers to the lagged dependent variables by one period. COM is the ratio of net fee and commission incomes to total operating income; TRA is the ratio of net trading income to total operating income; OTH is the ratio of net other operating income to total operating income. NIM indicates total interest income/total interest expenses. LTA is loans/total assets, and NON is the non-interest expenses/total assets. The Sargan test checks the null hypothesis, i.e., that the instruments used are not correlated with the residuals. AR (2) denotes the Arellano-Bond test for the 2nd-order autocorrelation in first differences. Figures in brackets present the standard error. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

	ROA	ROE	RAROA	RAROE	ROA	ROE	RAROA	RAROE	ROA	ROE	RAROA	RAROE
It-1	0.670***	0.527***	1.088***	0.954***	1.538***	0.400	0.990***	0.951***	1.167***	0.826***	1.064***	1.004***
	(0.050)	(0.150)	(0.019)	(0.018)	(0.131)	(0.204)	(0.109)	(0.095)	(0.039)	(0.135)	(0.041)	(0.044)
COM	0.020**	0.804***	0.197**	0.144**								
	(0.006)	(0.097)	(0.072)	(0.049)								
TRAD					0.036*	1.896	0.259	0.462*				
					(0.018)	(2.296)	(0.151)	(0.216)				
OTH									-0.023**	-0.756***	-0.073**	-0.195***
									(0.007)	(0.081)	(0.027)	(0.048)
NIM	0.031	0.058	-0.778*	-0.709***	-0.312**	6.267	1.303**	0.195	-0.247**	-3.971***	-0.707***	-0.975***
	(0.021)	(1.130)	(0.355)	(0.091)	(0.120)	(4.616)	(0.443)	(1.205)	(0.089)	(1.001)	(0.151)	(0.245)
LTA	-0.002	-0.353*	-0.154***	-0.132***	-0.032***	-0.053	-0.166*	-0.074	-0.012**	-0.158	-0.096**	-0.035
	(0.007)	(0.148)	(0.026)	(0.029)	(0.004)	(0.278)	(0.081)	(0.115)	(0.004)	(0.156)	(0.030)	(0.056)
NON	0.288***	7.786***	2.623***	2.013***	0.647**	-3.855	-2.751**	0.432	0.614***	10.016***	1.892***	1.874
	(0.053)	(0.708)	(0.752)	(0.454)	(0.234)	(8.401)	(0.919)	(3.229)	(0.183)	(1.517)	(0.457)	(1.161)
Constant	-0.112	9.103	4.803**	5.294***	1.250***	-3.068	7.255*	2.536	0.615***	14.258	4.913**	-0.195***
	(0.402)	(9.448)	(1.771)	(0.626)	(0.244)	(18.252)	(3.313)	(5.211)	(0.167)	(8.949)	(1.784)	(0.048)
F-test	0.000	0.000	0.000	0.000	0.000	0.000	0.087	0.002	0.000	0.000	0.000	0.000
Sargan test	0.999	1.000	0.999	0.998	1.000	1.000	0.996	0.996	1.000	1.000	1.000	0.779
AR(2)	0.116	0.317	0.154	0.243	0.125	0.158	0.111	0.258	0.162	1.000	0.102	0.249
Observations	44	42	44	42	43	41	43	41	44	42	44	42

The results in Table 3.12 and Table 3.13 presents the effects of components of non-interest activities on bank performance for D- and N-SIBs.

Table 3.12 shows that different types of non-interest business also have different impacts on the performance level of D-SIB banks. Specifically, fee and commission activities have a negative impact on bank performance. The results for transactions and other sub-activities show similar signs and directions to those for G-SIBs. However, as the level of income diversification is quite low relative to the level of fee collection activities, the expansion of such business has had a negative impact on bank performance.

As can be seen from the table, among the three components of non-interest income, the proportion of commissions and other non-interest activities is relatively large, resulting in a decline in the performance of small banks, while various types of banks benefit from further participation in trading activities when their performance improves. This finding is consistent with the previous results for medium-sized D-SIBs.

Table 3.12 Results for three components of non-interest income and bank performance for D-SIBs, 2005 to 2016

This table reports the two-step SYS-GMM dynamic panel estimation results with robust errors. Our dependent variables are return on assets (ROA), return on equities (ROE), risk-adjusted return on assets (RAROA), and risk-adjusted return on equity (RAROE). It-1 refers to the lagged dependent variables by one period. COM is the ratio of net fee and commission incomes to total operating income; TRA is the ratio of net trading income to total operating income; OTH is the ratio of net other operating income to total operating income. NIM indicates total interest income/total interest expenses. LTA is loans/total assets, and NON is the non-interest expenses/total assets. The Sargan test checks the null hypothesis, i.e., that the instruments used are not correlated with the residuals. AR (2) denotes the Arellano-Bond test for the 2nd-order autocorrelation in first differences. Figures in brackets present the standard error. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

	ROA	ROE	RAROA	RAROE	ROA	ROE	RAROA	RAROE	ROA	ROE	RAROA	RAROE
It-1	0.810***	0.330*	0.917***	0.672***	0.163	0.079	0.590***	0.527***	0.790***	0.218	0.897***	0.543***
	(0.063)	(0.152)	(0.039)	(0.062)	(0.448)	(0.108)	(0.083)	(0.069)	(0.048)	(0.198)	(0.051)	(0.069)
COM	-0.011***	-0.225*	-0.055***	-0.063*								
	(0.001)	(0.114)	(0.008)	(0.027)								
TRAD					0.053*	1.644	0.304**	0.431*				
					(0.022)	(0.887)	(0.114)	(0.191)				
OTH									-0.058**	-2.157**	-0.325***	-0.952*
									(0.018)	(0.744)	(0.098)	(0.414)
NIM	0.068***	2.599	0.462***	-0.024	0.426***	2.106	-0.372	-0.271	0.064	1.928	0.149	-2.418**
	(0.020)	(1.501)	(0.116)	(0.473)	(0.119)	(2.123)	(0.342)	(0.489)	(0.064)	(1.892)	(0.234)	(0.915)
LTA	0.002	-0.066	0.015*	0.023	0.006*	0.202***	0.057*	0.117**	0.007*	0.074	0.043*	0.033
	(0.002)	(0.064)	(0.007)	(0.026)	(0.003)	(0.055)	(0.028)	(0.040)	(0.003)	(0.078)	(0.019)	(0.035)
NON	0.075*	2.162	-0.061	0.801	-0.285	10.621**	2.562***	2.819**	0.193	7.107*	0.866	5.398**
	(0.034)	(2.393)	(0.185)	(0.968)	(0.157)	(3.651)	(0.529)	(0.916)	(0.101)	(3.588)	(0.444)	(1.870)
Constant	-0.034	8.693	-1.042*	0.271	-0.401	-9.999*	-2.676	-6.016*	-0.414*	0.553	-2.601**	2.934
	(0.102)	(6.272)	(0.468)	(1.734)	(0.436)	(4.011)	(1.491)	(2.457)	(0.188)	(7.283)	(0.964)	(2.284)
F-test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sargan test	1.000	0.334	1.000	0.923	0.939	0.656	0.861	0.967	1.000	1.000	1.000	0.978
AR(2)	0.849	0.110	0.271	0.134	0.772	0.488	0.487	0.140	0.932	0.181	0.351	0.151
Observations	99	97	99	97	97	95	95	95	99	97	99	93

Table 3.13 Results for three components of non-interest income and bank performance for N-SIBs, 2005 to 2016

This table reports the two-step SYS-GMM dynamic panel estimation results with robust errors. Our dependent variables are return on assets (ROA), return on equities (ROE), risk-adjusted return on assets (RAROA), and risk-adjusted return on equity (RAROE). It-1 refers to the lagged dependent variables by one period. COM is the ratio of net fee and commission incomes to total operating income; TRA is the ratio of net trading income to total operating income; OTH is the ratio of net other operating income to total operating income. NIM indicates total interest income/total interest expenses. LTA is loans/total assets, and NON is the non-interest expenses/total assets. The Sargan test checks the null hypothesis, i.e., that the instruments used are not correlated with the residuals. AR (2) denotes the Arellano-Bond test for the 2nd-order autocorrelation in first differences. Figures in brackets present the standard error. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

	ROA	ROE	RAROA	RAROE	ROA	ROE	RAROA	RAROE	ROA	ROE	RAROA	RAROE
It-1	0.440***	0.555***	0.657***	0.832***	0.411***	0.478***	0.822***	0.940***	0.594***	0.845***	0.986***	1.106***
	(0.062)	(0.031)	(0.085)	(0.093)	(0.051)	(0.017)	(0.063)	(0.025)	(0.029)	(0.027)	(0.053)	(0.078)
COM	-0.013**	-0.254***	-0.037*	-0.073***								
	(0.004)	(0.070)	(0.018)	(0.017)								
TRAD					0.010***	0.180*	0.159**	0.135***				
					(0.003)	(0.083)	(0.052)	(0.022)				
OTH									-0.022**	-0.418**	-0.222***	-0.330***
									(0.007)	(0.138)	(0.064)	(0.075)
NIM	0.140***	-0.094	0.182*	-0.083	0.190***	1.427*	-0.236	-0.496***	-0.059*	-2.411***	-1.203***	-1.164***
	(0.020)	(0.494)	(0.083)	(0.057)	(0.016)	(0.671)	(0.190)	(0.111)	(0.024)	(0.601)	(0.305)	(0.193)
LTA	-0.004*	-0.106*	0.003	-0.003	-0.002	-0.021	0.034***	0.012*	-0.001	0.137***	0.052***	0.052***
	(0.002)	(0.053)	(0.007)	(0.004)	(0.002)	(0.045)	(0.009)	(0.005)	(0.001)	(0.020)	(0.008)	(0.009)
NON	0.040	4.932*	0.790**	0.590*	0.018	0.661	1.072***	1.392***	0.553***	6.752***	2.003***	1.200**
	(0.065)	(2.234)	(0.273)	(0.266)	(0.054)	(1.637)	(0.298)	(0.277)	(0.047)	(0.992)	(0.463)	(0.442)
Constant	0.386***	9.772***	0.779	0.857**	0.122	6.228*	-1.145*	-0.212	0.210***	-1.407	-0.218	-0.143
	(0.099)	(2.597)	(0.551)	(0.318)	(0.092)	(2.953)	(0.521)	(0.289)	(0.038)	(0.889)	(0.273)	(0.544)
F-test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sargan test	1.000	1.000	0.992	1.000	0.989	0.652	0.971	1.000	0.997	1.000	1.000	1.000
AR(2)	0.163	0.541	0.741	0.799	0.220	0.337	0.258	0.384	0.671	0.422	0.371	0.593
Observations	276	276	276	276	270	270	270	270	274	274	274	274

We suggest that banks of different type and size receive different diversification effects with different components of non-interest activities. Trading activity can bring benefits in terms of performance improvement for the overall banking sector and for all three sub-groups. However, we see that the proportion of trading activities in banks' income stream is still relatively low, especially for large and medium-sized banks, which are still paying more attention to fee-based activities. While such a diversification strategy can work well for G-SIBs, as they have already accumulated enough specialists and established a well-regulated risk management system, D-SIBs will eventually suffer a performance discount from too great an expansion of fee-based income. Therefore, rather than engaging blindly in diversification activities, banks' managers should select the most appropriate diversification direction and strategy by considering their own situation and businesses scope. Furthermore, regulators should develop more detailed supervisory plans and guidance for banks' diversification process by subdividing the components of non-interest business and taking into account the impact of different types of non-interest business on different types of banks.

3.5 Conclusion

This chapter examines to what extent income diversification can affect performance in the Chinese banking industry. Employing a dynamic SYS-GMM panel data model to evaluate the performance effects of income diversification, this chapter finds existence of a diversification discount in the Chinese banking sector as a whole, suggesting that a shift from traditional banking business to mixed business lines negatively affects bank performance.

However, structurally, the results are rather diverse. After separating the sample banks into three groups, we find that the largest Chinese banks, China's global systemically important banks or G-SIBs, can improve their performance by using diversification. The next group, the domestic systemically important banks or D-SIBs, shows a nonsignificant performance response to the shifting to mixed business lines. The most important under-performer is China's non-systemically important banks or N-SIBs. The key factor that drives the performance differences lies in the banks' capability to reap the benefits of diversification through the learning-by-doing process. Other factors include size of the bank, regulatory differences and the extent of moral hazard.

After decomposing non-interest activities into three components (fee-based, trading and other activities), it is found that, for the Chinese banking market as a whole, fee-based and other income activities lead to a diversification discount, and that only G-SIBs can obtain benefits from diversification towards fee and commissions. However, trading activities can always improve banks' performance level, for both the entire Chinese banking sector and its three sub-groups. Therefore we suggest that banks' managers and regulatory authorities should set different diversification strategies and regulatory policies based on these diversification differences, so as to ensure that both specific banks and the entire banking system can maintain a higher profitability level.

Chapter 4

Chapter 4 Income Diversification and Bank Risk

This chapter investigates to what extent income diversification affects the risks of Chinese banks. First, this research measures both idiosyncratic risk and financial distress for specific banks. Then, it adopts the first-differenced GMM method based on the threshold dynamic panel model to investigate the income diversification effects on banks' risk level.

Chapter 4

Income Diversification and Bank Risk

In Chapter 3, an investigation focused on the diversification-performance nexus found that there exists an overall harmful diversification effect in the Chinese banking market. The Chapter also identified that, in addition to the in-depth consideration of profitability, banks engaging in income diversification must give due attention to the key aspect of safeguarding with regard to banks' idiosyncratic risk and banks' financial distress. Chapter 4 assesses the effects of income diversification on risk among Chinese banks. Using the threshold dynamic panel estimator based on the first-differenced GMM method, we find that for the overall Chinese banking sector, results reveal the existence of an inverse U-shaped relationship between bank risk and income diversification in terms of both banks' idiosyncratic risk and banks' financial distress.

4.1 Introduction

Non-interest activities have become an important source of revenue for banks in mature as well as emerging markets in recent decades (Stiroh, 2004; Laeven and Levine, 2007; Sanya and Wolfe, 2011, DeYoung and Torna, 2013 and Doumpos, et al., 2016). Lately, bank diversification has also gained momentum in China. With the gradual development of market-oriented financial reform, Chinese banks are now actively engaged in non-interest business, including underwriting, brokerage and fiduciary services (Berger, et al., 2010a; Li and Zhang, 2013, and Chen, et al., 2017). As a result, while the traditional lending business continues to be their main source of revenue, Chinese banks are steadily shifting towards a multiple-revenue structure. Given the growing importance of business diversification for Chinese banks, it is imperative to study the risk implications of such a significant development.

While the prior literature has indicated diversification can be beneficial for banks, debates remain as to whether and how the diversification-risk nexus are affected when banks move into non-traditional businesses. Earlier studies find a potential risk reduction from increasing the proportion of non-interest income (DeYoung and Roland, 2001; Stiroh and Rumble, 2006). However, recent research suggests that the inter-relatedness among banks' non-interest products and services could mean a higher correlation, so a cross-selling strategy would result in excessive risk that could not be offset by portfolio diversification (Chen and Zeng, 2014). Moreover, non-interest income may also mean other risk-enhancing factors, such as that they could be more volatile owing to high-financial leverage (DeYoung and Roland, 2001), that there could be increased asymmetric information between the bank and borrowers (Mercieca et al., 2007), and that it is easy for customers of non-interest activities to switch to another bank (Li and Zhang, 2013).

This chapter aims to foster a better understanding of banks' diversification and risk nexus through the case of Chinese banks. Existing studies focus mainly on mature markets. Few studies have focused on the diversification effect in the Chinese banking industry. This leaves a critical void in the literature, particularly in light of the growing importance of the nation's banking industry, which has surpassed Europe to become the world's second largest, following that of the US.

We extend the current literature by developing an advanced methodology to address the particularity of China's institutional background and data characteristics. Existing studies on bank diversity and risk have included very few considerations of dynamics in their relationship, with most adopting a static panel data model using either ordinary least squares regression (Berger et al., 2010b) or fixed effect estimation (Zhou, 2014). Nevertheless, this research shows banks' risk characteristics can generate dynamic changes. Specifically, we employ the first-differenced GMM estimator of dynamic panel models with threshold effects. This estimator addresses the inconsistencies generated from the endogeneity problem, providing a non-linear view of the dynamic GMM (Hsiao and Zhang, 2015). The method addresses the endogeneity of both regressors and transition variables that are unlikely to be achieved by employing the standard least squares approach (Seo and Linton, 2007). Moreover, this approach avoids the bias from quadratic terms that are widely used in the field; see Acharya et al. (2006), Gamra and Plihon (2011) and Brei and Yang (2015).

Our findings show the existence of a non-linear diversification effect on banks' idiosyncratic risks and the probability of banks' financial distress and to several reasons. Consistent with Acharya et al. (2006), a bank's monitoring effectiveness might be lower in newly entered and competitive sectors, so the diversification may initially lead to a poorer quality of the loan portfolio and higher potential operational risk. Over time, however, this diversification discount will gradually change to a diversification benefit. Second, the inverted U-shaped relationship may also be caused by the learn-by-doing effect. Learning can be a dynamic process, and banking institutions gradually understand specific characteristics of the business lines and the risk levels thereof, and thus, what proportion of non-interest income is most suitable to them (Gamra and Plihon, 2011). With richer experience, the benefits of diversification across various sources of earnings would offset the costs of increased complexity and the associated idiosyncratic risk.

Size does matter for banks diversifying into new businesses other than traditional interest earning activities (Chiorazzo et al., 2008 and De Jonghe et al., 2015). Our sample comprises 35 Chinese commercial banks and are divided into three sub-groups: Global Systemically Important Banks (G-SIBs), Domestic Systemically Important

Banks (D-SIBs), and banks that are not classified by the authorities as systemically important (N-SIBs) to capture this effect.

The remainder of the chapter is organized as follows. Section 4.2 provides an overview of relevant literature on bank risk and income diversification. The data on variables and the methodology are presented in Section 4.3. Section 4.4 outlines the model specification and reports the empirical results. Section 4.5 offers concluding remarks.

4.2 Related Literature

Theoretically, diversification of income sources can improve the stability of banks' cash flows and disperse their idiosyncratic risks. Stiroh (2004) maintains that the traditional lending business provides a channel for banks to attract clients to their non-interest activities, as people are more likely to seek fee-based services in the same bank. Wagner (2010) shows that banks are keen to adopt a strategy that uses attractive lending and deposit rates to improve customer stickiness and to make themselves more profitable through high-return non-interest income. Pennathur et al. (2012) suggest that combining the two business assets into a portfolio can be mutually beneficial and there would not be crowd-out effects between them. Given that non-interest and interest incomes are not perfectly correlated, a portfolio of these activities can be risk reducing. In addition to the portfolio effect, diversified banks can also obtain rich information from their mixed business lines. Use of the information can help banks improve risk management (Stein, 2002; Elsas et al., 2010).

However, some authors argue that fee-earning activities could be associated with higher risk than are interest activities, as they will increase the overall volatility of the portfolio (Stiroh and Rumble, 2006; Demirgüç-Kunt and Huizinga, 2010; and Köhler, 2014). One reason for the increase in volatility is that income from non-interest activities may have greater fluctuation, because it is easier for clients to switch between banks in these activities than in lending activities (Lepetit et al., 2008). In the face of cyclical fluctuation, non-interest income would decrease dramatically, while banks with a larger proportion of interest activities might maintain a more stable performance compared with more diversified banks (Köhler, 2014). Another reason is that non-interest activities require less regulatory capital, which may lead banks to have a higher degree of financial leverage and, hence, may increase earnings volatility (DeYoung and Roland, 2001). In addition, an agency problem may also play a role here. Given interest conflicts with shareholders, managers have incentives to over-diversify, which will, in turn, harm the wider financial system because diversification makes institutions become more similar to each other by exposing them to the same risks, which may cause a joint failure (Acharya and Yorulmazer, 2008; Wagner, 2010).

Empirical evidence on whether fee-earning activities would increase banks' risk has been mixed. Chiorazzo et al. (2008) show positive evidence suggesting that diversification can improve the trade-off between risk and income for Italian banks.

Köhler (2014, 2015) finds that banks' earnings will be more stable and profitable if they diversify into noninterest income. Similar results are also reported in Mergaerts and Vander (2016) and Nguyen et al. (2016). Recent research suggests that revenue diversification could also be beneficial to banks from developing countries (Sanya and Wolfe, 2011).

Conversely, negative evidence has been found by an extensive body of research. Many studies focusing on US banks find that diversification fails to produce a greater performance. Such research includes DeYoung and Roland (2001), DeYoung and Rice (2004), Stiroh (2004), Stiroh and Rumble, (2006), Acharya et al. (2006), Hayden et al. (2007), Mercieca et al. (2007), Goddard et al. (2008), and Berger et al. (2010a, b). For risk implications, evidence of an adverse relationship between diversification and risk of American banks has been presented in, for example, Demsetz and Strahan (1997), and DeYoung and Roland (2001). Baele et al. (2007), analysing a panel data of banks during 1989-2004, find that a higher share of non-interest income positively affects bank' franchise values, but increases their systematic risk. Lepetit et al. (2008) suggest that diversified banks present higher risk than banks mainly conducting traditional business, though this positive link between diversification and risk is largely a phenomenon of small banks and driven by commission activities.

Another strand in the empirical literature explores the phenomenon whereby, although the non-interest income as a whole may lead to benefits or discount, the bank risk estimation varies among different activities under non-interest income. Stiroh (2004) divides non-interest income into three components, namely, fee-for-service income, trading revenue, and other types of non-interest income, and suggests that these different activities could have different effects on risk. Lee et al. (2014) consider 29 Asia-Pacific banking markets and identify that risk derives mainly from commission and fee activities, and that trading and other non-interest incomes could reduce banks' risk level. Similarly, Meslier et al. (2014) investigate an emerging country sample from 1999 to 2005. They estimate valuation variability of a bank's stock returns and find that increasing the share of fee-based income leads to a risk increase. From the view of Elyasiani and Wang (2008), such fee-for-service income makes banks less transparent to investors and, thus, makes the task of bank supervision more difficult.

Recently, researchers have started to examine whether the effect of diversification differs according to bank-specific characteristics, such as size and types. By using the GMM system, Goddard et al. (2008) suggest that a similar cross-selling strategy is not suitable for both large and small credit unions. With the same method, Chen and Zeng (2014) show that small-sized banks in the EU banking industry are restricted to selected market segments; thus, smaller banks may be associated with a higher risk exposure and higher default risk than are larger banks. Similarly, Köhler (2014) find that larger banks are more likely to be active in volatile and risky trading and off-balance sheet activities, which allows them to employ a higher financial leverage than small banks. In addition, some studies also claim that size increase due to diversification could make the financial system more fragile. Small-sized banks are highly susceptible to the failure of large banks, which poses a high external risk for the entire financial sector (Kobayashi, 2012). However, as suggested by Gurbuz et al. (2013), large-sized banks generally have better information technology, human capital management and risk management. Therefore, diversified bank with larger size could cause technology spillover and create advantages from the economy of scope, thus outperforming others within the banking industry (Mercieca et al., 2007).

Mixed findings on the risk profiles of banks' revenue diversification suggest that while diversification into fee-earning activities may be beneficial to some banks, it has a dark side since the volatile non-interest income may offset the benefits due to the portfolio effect (Stiroh and Rumble, 2006). In this light, further empirical investigation into the effect of revenue diversification on bank risk would be desirable and necessary.

The static panel data analysis is based on both accounting and stock market data, and the estimation methods used ranges from pooled OLS (Lepetit et al., 2008; Kobayashi, 2012) to fixed effects (Bonin et al., 2005; Tabak et al., 2011) and random effects GLS estimation (Mergaerts and Vander, 2016). However, the approach suffers from the endogeneity problem because diversification strategies are correlated with banks' business opportunities (Acharya et al., 2006; Stiroh and Rumble, 2006; Baele et al., 2007; Busch and Kick, 2009, Sanya and Wolfe, 2011; Köhler, 2014). In 1995, Berger and Ofek identified a diversification discount without controlling for endogeneity. Subsequent papers, however, find that with consideration of the endogeneity problem, they obtain an inverse result; that is, the result becomes positive with the same methodology (Campa and Kedia, 2002 and Villalonga, 2004),

To address endogeneity and other estimation inconsistences in the banking context, many studies then select to employ dynamic panel models, or the generalized methods of moments (GMM) estimator. Research in this strand of the literature includes Sanya and Wolfe (2011), Nguyen (2012), Vallascas and Keasey (2012) and Gambacorta et al. (2014) to name just a few.

Recent studies noted the existence of a non-linear relationship between diversification and banks' risk (Demirgüç-Kunt and Huizinga, 2010; Gamra and Plihon, 2011). A common method to capture such a non-linear relationship is to include a quadratic term in the empirical model (Gambacorta et al., 2014; Brei and Yang, 2015). Acharya et al. (2006) add a risk-squared variable ($Risk^2$) in the regression specification. Baele et al. (2007) introduce the square of non-interest revenue share into their empirical model. Importantly, these models shed light on the nonlinear nature of the banks' diversification-risk nexus, but the banks' income diversification as a process could be not only nonlinear but also dynamic. However, these terms are exogenously given in nature, and may thus be inadequate for treating the endogeneity problem. Furthermore, it is plausible that diversification would only start to exert its effects beyond some threshold levels. This finding implies that consideration of the threshold effect in a dynamic nonlinear model is also required.

4.3 Data and Methodology

4.3.1 Data Sample

Our chapter sample comprises an unbalanced panel of annual report data from 35 Chinese banks over the period from 2007 to 2016. Following the Guidelines for the Disclosure of Global Systemic Importance Indicators of Commercial Banks issued by the China Banking Regulatory Commission (CBRC), these commercial banks can be divided into three groups: global systemically important banks (G-SIBs), domestic systemically important banks (D-SIBs), and other banks (N-SIBs).

The reason for choosing 35 banks from 2007 to 2016 rather than 40 banks from 2005 to 2015 as in Chapter 3 and Chapter 5 is that the first-differenced GMM estimator for the dynamic threshold panel data model requires balanced data. Of the 40 banks used in those chapters, five did not exist before 2007. Therefore, in order to maximize the data, the observation period is reduced by two years, and the sample includes only those banks that were established in or before 2007.

In this chapter, all balance sheet and income information used to construct the variables for empirical analysis are taken from Bankscope. Daily market and bank stock returns are taken from DataStream International. Industry-specific and macroeconomic data are obtained from the National Bureau of Statistics of China.

4.3.2 Variables

1) Dependent Variables (1): Idiosyncratic Risk Measures

First this chapter adopts two accounting-based idiosyncratic risk indicators which are widely used in the empirical banking literature, namely, the ratio of loan loss provisions and customer loans (LLP) and the ratio of impaired loans and equity (ILE). As suggested by Hsieh et al. (2013), with such a traditional measure, a higher value indicates that the bank has higher level of risk for its loan portfolio.

In order to find out which specific risk would be affected by income diversification, we also divided the non-systemic risk into three catalogues including credit, liquidity and interest rate risks. Following Valverde and Fernández (2007), we also divided the non-systemic risk into three categories, including credit, liquidity and interest rate risks. Credit risk (CREDIT) is calculated as the one-lagged ratio of loan default to total loans. Liquidity risk (LIQUIDITY) is the ratio of liquidity assets to short term funding, and interest rate risk (INTEREST) refers to the changes in the three-month interbank market rate.

2) Dependent Variables (2): Financial Distress Measures

Recent studies of diversification effect also tend to take account of financial distress (such as DeYoung and Torna, 2013), in order to achieve a deep understanding of banks' default and insolvency risk. Two commonly used measures to detect such financial distress are the Z-score and distance to default. The former is a popular measure of soundness of a bank because it combines the bank's buffers such as capitalization with returns and volatility, and hence allows investigation of bank risk and stability. Studies employing the Z-score to measure the probability of bank insolvency and bankruptcy include Berger et al. (2009), Laeven and Levine (2009), Angkinand and Wihlborg (2010), Barry et al. (2011), and Demirgüç-Kunt and Huizinga (2010). Following Lepetit et al. (2008), the original Z-score can be extended to become the ZP-score by including a risk index to investigate various bankruptcy-related scenarios.

The DD indicator quantifies bank distress by gauging how far a firm is from default and is widely used for measuring default risk (Vassalou and Xing, 2004; Hovakimian et al., 2012). Recently, it has also been applied to check the soundness of Chinese banks (Chen et al., 2010; Lv and Tang, 2014). As a risk predictor, it has been verified as useful by numerous studies and its predictive power with regard to bank fragility outperforms that of several accounting and market-based measures (Campbell et al., 2008; Bharath and Shumway, 2008). The DD index is generally calculated according to the KMV-Merton model for listed banks and Private Firm Model (PFM) separately.

Both distance to default and ZP-score have an inverse correlation with financial distress and banks with a higher DD and ZP-score are less likely to default. Therefore, our study uses the opposite of DD and ZP-score to measure the risk level which would have the same direction with that of LLP and other risk indicators.

3) Independent Variables: Measures of Income Diversification

Similarly to Mercieca et al. (2007), our study measures the level of income diversification by constructing a Herfindahl-Hirschman index (HHI). We also divide the non-interest income into three categories: revenue from trading in foreign exchange and fiduciary activities; fee and commission income gained from clearing, settlement and other financial services; and other non-interest income. Our construction of the HHI index follows Elsas et al. (2010). Conversely, the diversification levels are measured respectively along the three categories of income. Following Köhler (2014), we also construct the diversification index by employing the ratio of net fee and commission income to total operating income (COM), the ratio of net trading income to total operating income (TRA) and the ratio of net other operating income to total operating income (OTH).

4) Control Variables

LCD: This variable is the ratio of loans to customer deposits. According to Cornett et al. (2010), this ratio can reflect the level of banks' liquidity. The larger the ratio is, the lower the level of liquidity will be.

ETA: To adjust for banks' attitude towards risk, we adopt the ratio of equity over assets, which describes the degree of total financial leverage and capital adequacy (Stiroh, 2004; Pennathur et al., 2012; Gurbuz et al., 2013). According to Busch and Kick (2009), a well-capitalized bank is less likely to become insolvent and more likely to be engaged in low-risk investment to ensure that it operates soundly.

CIR: Cost-income ratio is estimated through the operating expenses relative to gross income which measuring banks' cost structure (Busch and Kick, 2009).

4.3.3 Methodology

Prior research in the field is mostly focused in static analysis. However, banks' income diversification is a long process, during which the evolvement of the diversification-risk nexus could be dynamic and non-linear. In addition, there may exist a threshold effect since it is plausible that only beyond some threshold level would diversification start to have a significant effect on bank risk. This finding implies that the static and linear method could be inadequate for capturing the risk implications of diversification. Rather, a dynamic threshold model would be more fitting.

In this study, a GMM-type threshold model, or the first-differenced GMM estimator for the dynamic threshold panel data model, as proposed by Seo and Shin (2016), is employed. This approach has the advantage of giving a dynamic view of the diversification effects on bank risk while avoiding both the endogeneity problem usually associated with the static model and the bias from using the quadratic terms as proxy for the non-linear relationship. It can also overcome the problem associated with previous GMM-type threshold models, whereby both regressions and threshold variables must be exogenous (Ramírez-Rondán, 2015).

The research proceeds by assuming nonlinearity in Chinese banks' diversification-risk nexus for two reasons. First, Chinese banks on the whole are still in the early stages of diversification. When a bank first begins to engage in non-interest activities, managers generally lack the necessary skills and professionalism. Given the circumstances, some decisions may be irrational, exposing the bank to excessive risks (Deng and Li, 2006). Second, with under-developed governance structure, moral hazard is more likely to emerge, leading to inefficient allocation of resources and over-diversification (Barry et al., 2011). However, over time, this excess may be gradually mitigated with both the expanding of diversification and obtaining of better information among a bank's management. Consequently, the diversification effects can be non-linear and vary with the changing proportions of non-interest activities.

Conventional econometric approaches to capturing such a non-linear relationship are to catalogue different groups with 25th, 50th, and 75th percentiles of non-interest income shares (Chiorazzo et al., 2008) or to include quadratic terms in empirical models (e.g., Gambacorta et al., 2014; Brei and Yang, 2015). However, use of such proxies cannot provide consistent results in the face of a certain threshold value. Rather, a threshold model would be more appropriate in that it treats the sample split value as unknown.

Tong (1978) first developed the threshold auto-regression (TAR) model for use in time-series analysis. This method estimates the threshold variables to determine the threshold point and to avoid the bias generated from using a subjective approach to determine the critical value for each group. The static threshold model has subsequently been developed to cover cross-sectional and panel data (e.g., Tiao and Tsay, 1994; Martens et al., 1998; Hansen, 1999). The most widely used threshold estimation, developed by Hansen (1999), employs a framework with a panel dataset $\{y_{it}, q_{it}, x_{it}: 1 \leq \mathrm{i} \leq \mathrm{n}, 1 \leq \mathrm{t} \leq \mathrm{T}\ \}$, where y_{it} refers to the dependent variable, q_{it} is a scalar of threshold variable and x_{it} represents the vector of all control variables included in the regression. In setting this model, all regressors, including the threshold variables, are required to be exogenous. To estimate the regression slope, Hansen (1999) adopts the OLS estimation with restrictions on x_{it} and q_{it} being time variant.

Research finds high-risk banks are more likely to enter into riskier industries and produce riskier loans (Acharya et al., 2006). This endogeneity bias proves to exist both in the decision to diversify and in systematic differences between different types of banks. Based on Hansen (2000), Caner and Hansen (2004) develop an asymptotic framework and employ a two-stage least square estimation to address the endogeneity problem. Subsequent studies have followed this two-stage least square method.

However, the improvements offered by this method remain limited in that both regressors and threshold variables have to be exogenous (Seo and Linton, 2007; Yu, 2012). In response, recently several studies have attempted to address this endogeneity problem of threshold variables by employing the dynamic threshold regression model. Kourtellos et al. (2016) constructed a two-stage concentrated least squares method. Yu and Phillips (2018) addressed the endogeneity problem by introducing the integrated difference kernel estimator (IDKE). Ramírez-Rondán (2015) proposed a maximum likelihood estimation of the threshold with slope parameters. In our study, the non-linear effect is estimated by using the first-differenced GMM threshold dynamic panel model based on Seo and Shin (2016). This method provides a dynamic and non-linear view over the relationship between income diversification and risk. By adopting the two-step first-differenced GMM estimator, it overcomes the endogeneity bias and allows for both regressors and threshold variables to be endogenous.

4.4 Empirical Estimation and Results

4.4.1 Estimation Steps

To estimate the parameters, Seo and Shin (2016) applied a two-step GMM estimation procedure for the estimation of a non-linear relationship. First, for the value of a selected threshold variable γ, $\theta = (\phi, \beta_1, \beta_2, \delta\ )$ is estimated through the first-difference GMM by using the instruments suggested by Arellano and Bond (1991). Second, this estimation is repeated for γ 's belonging in a strict subset of the support of the threshold variable. Therefore, it is possible to calculate a different $\hat{\theta}$ for each selected γ. Under this condition, the parameter value of γ could minimize the GMM-type objective function; thus, $\hat{\theta}$ can be defined as the two-step optimal GMM estimator. The GMM-threshold estimator is employed in a non-linear setting, which allows for endogenous regressors and endogenous threshold variables. The estimator overcomes the drawbacks of previous methods that fail to take into account the endogeneity problem leading to biased estimation.

Two tests are necessary for the model. First, a Hausman type test is used to check the validity of the over-identifying moment conditions. Under the null hypothesis, models have effective instruments and avoid over-identifying restrictions. In that case, instruments in the GMM models are appropriately orthogonal to the error and are therefore reasonable and statistically acceptable. Second, we test for linearity or threshold effects as a result of the presence of unidentified parameters.

4.4.2 Overall Results

4.4.2.1 Income Diversification and Risk: Whole Sample

Table 4.1 below reports the regression results between the diversification level and four different bank risk measures. Coefficients of control variables appear largely reasonable. According to the regression results for variables with idiosyncrasy risk (Model 1 and Model 2), the threshold estimations are 20.166 and 12.158, respectively. One can see that the diversification level is positively correlated with banks' idiosyncratic risk, while at the same time, higher levels of diversification are associated with a reduction in bank risk.

In general, our study echoes the work of Gamra and Plihon (2011), who use data from both East Asian and Latin American markets and find that income diversification makes banks less stable in the early stages of engaging in mixed business lines, but that they become more stable with the expansion of non-interest activity.

Table 4.1 Income diversification and risk for Chinese banks from 2007 to 2016

This table reports the first-differenced GMM threshold dynamic panel model developed by Seo and Shin (2016). Our dependent variables are loan loss provisions/customer loans (LLP), impaired loans / equity (ILE), opposite distance to default (DD) and opposite Z-score. It-1 refers to the lagged one period of the dependent variables. HHI indicates the income diversification using Herfindahl-Hirschman Index with the components of interest income and three activities under non-interest income. LCD is Loans / Customer Deposits, ETA refers to Equity / Total Assets, CIR is Cost to Income Ratio. J-statistic checks the null hypothesis, i.e., that the instruments used are not correlated with the residuals. Linearity test checks whether threshold exists. Figures in brackets present the standard error. ***, ** and * indicate significance at the 1%, 5% and 10% level.

	Idiosyncratic Risk		Financial Distress	
	ILP	LLE	Z-score	DD
	(1)	(2)	(3)	(4)
	Lower Regime			
It-1	-0.457*	-1.142*	1.744***	5.049***
	(0.252)	(0.630)	(0.493)	(1.931)
HHI	0.036	0.736*	0.067	1.072***
	(0.025)	(0.379)	(0.049)	(0.399)
LCD	-0.116***	0.275	-0.010	-1.462***
	(0.033)	(0.294)	(0.028)	(0.444)
ETA	0.090***	0.667*	0.092	0.174
	(0.028)	(0.359)	(0.099)	(0.199)
CIR	-0.202**	1.999	-0.486	-1.344
	(0.098)	(1.331)	(0.439)	(1.598)
	Upper Regime			
It-1	1.351***	-3.607***	1.317***	-1.727***
	(0.400)	(0.936)	(0.317)	(0.405)
HHI	-0.123***	-1.032**	-0.054**	-0.101
	(0.037)	(0.480)	(0.022)	(0.237)
LCD	-0.030	1.547***	0.111***	-0.762**
	(0.025)	(0.380)	(0.041)	(0.338)
ETA	0.047***	0.570	-0.026***	-0.853***
	(0.018)	(0.391)	(0.099)	(0.181)
CIR	-0.468	1.645	-0.391	1.563
	(0.333)	(1.684)	(0.365)	(1.456)
Threshold	20.166***	23.104***	19.048***	21.569***
	(0.792)	(1.580)	(7.082)	(1.244)
J-statistic	0.443	0.616	0.165	0.356
Upper Regime	0.273	0.174	0.329	0.223
Linearity test	0.014	0.001	0.022	0.000
Observations	315	315	315	315

These results can be explained from several perspectives. First, the process of diversification generates moral hazard problems and monitoring difficulties. Especially in the early stages of diversification ineffective monitoring make it difficult for both insiders and outsiders to observe the running of bank operations, which will have adverse impacts on bank risk. As the diversification in non-interest activity develops and hence the proportion of non-interest over total operational income increases, banks become more motivated to continually improve the governance and supervision regime to ensure that non-interest activity is not used in ways that would deteriorate both specific risk and financial stability (Ashraf et al., 2016).

Second, expansion of non-interest activities requires employees to have special knowledge, and the application of relatively advanced technology. Banks can reduce the risks through accumulation of sufficient experience and by studying the risk characteristics of non-interest activities and get benefits from leveraging managerial skills (Iskandar-Datta and McLaughlin, 2007). Furthermore, several advanced non-interest activities, such as securitization, can reduce possible shortfalls on payments to debtholders. However, such activities can be launched and supply a buffer to absorb losses only when banks have enough professional employees. To date, very few such non-interest activities have been launched in the Chinese banking sector. On the other hand, it is likely that, with the accumulation of experience and increased diversification, such advanced non-interest activities could make banks safer and more stable.

In this chapter, we also take account of the diversification effect on banks' financial distress. Table 4.1 reports the results by using Model 3 and Model 4 with consideration of financial distress. We find that non-traditional banking activities have economically meaningful effects on the probability of bank failure, and again, the results confirm the inverse U-shaped relationship between diversification and bank risk.

These results can be explained as follows. The calculation method for distance to default considers banks' debt level and whether or not the cash flow state is healthy. In the early stages of expansion of non-interest activities banks incur high initial costs, for example for the establishment of infrastructure and electronic platforms, and for specialist staff training. However, according to the empirical results reported from chapter 3, the non-interest income cannot make the overall Chinese banking industry more profitable. Therefore, the results of Models 3 and 4 reflect a situation in which, in the early stage, the process of income diversification will not bring benefits to alleviate banks' financial distress. However, with an increased level of non-interest activities, the initial costs can bring sustained profit and cash flow. Meanwhile, banks' debt is mainly generated from deposit and other interest businesses. Hence, the mixed business lines strategy also plays a role in reducing bank debt and increasing the overall liquidity level. Therefore, once the income diversification has passed a certain threshold, it makes banks more stable and reduces their financial distress.

4.4.2.2 Income Diversification and Risk: Evidence on China's Global, Domestic and Non-Systemically Important Banks

Table 4.2 reports the results from estimating the association between income diversification on one hand, and insolvency risk and financial stress on the other for G-SIBs, D-SIBs and N-SIBs during the period 2007-2016[4]. The results from the GMM type dynamic threshold estimation indicate that diversification is an important determinant of banks' risk indicators, but presents different diversification effects in different groups.

China's Global Systemically Important Banks

According to the results reported in Table 4.2, in contrast to the results for the whole sample, for G-SIBs the coefficients of the HHI are significantly and negatively associated with both idiosyncratic risks and financial distress. This is the case for both the lower and higher regimes.

[4] As the small sample size might result in an incidental parameters problem, this thesis also applies a robustness test by using dummy variables to the catalogue of the three sub-groups. The robustness test results are reported in the Appendix.

However, in the upper regime the coefficients of both risk indicators are higher than those in the lower regime. This indicates that Chinese G-SIBs will always gain risk-reduction benefits when diversifying into non-traditional businesses, but that after passing a certain threshold point of income diversification, risks will reduce even further, helping G-SIBs to improve their financial situation.

Such diversification benefits are in line with our first empirical results, where the mean of HHI for G-SIBS is 25.125, which is higher than the threshold point for all four models in Table 4.2. Therefore we suggest that, unlike the other two groups, G-SIBs have already passed the threshold point from diversification discount to diversification benefits. However, greater diversification could lead to yet further reduction of risk.

Table 4.2 Income diversification and risk for Chinese G-SIBs, D-SIBs and N-SIBs, 2007 to 2016

This table reports the first-differenced GMM threshold dynamic panel model developed by Seo and Shin (2016). Our dependent variables are loan loss provisions/customer loans (LLP), impaired loans / equity (ILE), opposite distance to default (DD) and opposite Z-score. It-1 refers to the lagged one period of the dependent variables. HHI is the income diversification using Herfindahl-Hirschman Index with the components of interest income and three activities under non-interest income. LCD is Loans / Customer Deposits, ETA refers to Equity / Total Assets, CIR is Cost to Income Ratio. J-statistic checks the null hypothesis, i.e., that the instruments used are not correlated with the residuals. Linearity test checks whether threshold exists. Figures in brackets present the standard error. ***, ** and * indicate significance at the 1%, 5% and 10% level.

	G-SIBs				D-SIBs				N-SIBs			
	Idiosyncratic Risk		Financial Distress		Idiosyncratic Risk		Financial Distress		Idiosyncratic Risk		Financial Distress	
	ILP	LLE	Z-score	DD	ILP	LLE	Z-score	DD	ILP	LLE	Z-score	DD
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Lower Regime											
It-1	0.195***	1.616***	0.692***	-0.007**	-0.716*	7.587***	1.101***	0.187	-1.253***	-1.057*	0.059	0.107
	(0.019)	(0.004)	(0.058)	(0.004)	(0.383)	(0.933)	(0.236)	(0.274)	(0.275)	(0.564)	(0.291)	(0.168)
HHI	-0.057***	-0.426***	-0.067***	-1.781***	0.311***	1.083***	0.018**	0.047	0.330***	0.501	0.270**	0.027*
	(0.002)	(0.013)	(0.004)	(0.011)	(0.066)	(0.318)	(0.009)	(0.043)	(0.049)	(0.328)	(0.126)	(0.015)
LCD	-0.059***	2.297***	-0.027**	-2.297***	-0.265***	2.270**	0.006	0.532***	-0.182***	0.431**	-0.124**	0.057***
	(0.003)	(0.007)	(0.014)	(0.015)	(0.046)	(1.106)	(0.005)	(0.05)	(0.057)	(0.212)	(0.062)	(0.02)
ETA	0.005***	1.717***	-0.035***	-0.793***	-0.232***	-0.503*	-0.052**	-0.064	0.162***	0.354	-0.205***	0.024
	(0.001)	(0.011)	(0.007)	(0.005)	(0.061)	(0.259)	(0.025)	(0.052)	(0.034)	(0.273)	(0.030)	(0.017)
CIR	0.371***	-11.08***	-0.481***	8.078***	1.547***	-31.442**	-0.540***	-3.806***	-0.698***	1.973	0.260*	-0.287***
	(0.012)	(0.047)	(0.082)	(0.057)	(0.150)	(15.556)	(0.079)	(0.239)	(0.173)	(1.31)	(0.150)	(0.057)

Table 4.2 (continued)

	Upper Regime											
It-1	-0.335***	6.945***	-0.194***	1.624	3.035***	0.746***	1.108***	4.050***	5.742*	-3.925**	-0.140	-2.043***
	(0.061)	(1.990)	(0.053)	(1.184)	(0.682)	(0.209)	(0.248)	(0.546)	(3.045)	(1.924)	(0.303)	(0.394)
HHI	-0.063***	-0.623	-0.157***	-2.192***	-0.143	-0.347	-0.063***	-0.253***	-1.304***	-2.066***	-0.165***	-0.030**
	(0.005)	(0.742)	(0.004)	(0.255)	(0.091)	(0.221)	(0.011)	(0.096)	(0.477)	(0.568)	(0.052)	(0.015)
LCD	-0.057***	2.521***	0.104***	-1.578**	-0.241***	0.704**	-0.001	0.335***	-0.125	1.603**	-0.138***	0.028***
	(0.003)	(0.312)	(0.014)	(0.613)	(0.034)	(0.304)	(0.004)	(0.037)	(0.082)	(0.788)	(0.032)	(0.009)
ETA	-0.036***	-0.945***	-0.047***	-2.325***	-0.005	0.777***	0.028**	0.271***	0.562***	0.451**	0.027	0.048***
	(0.002)	(0.350)	(0.002)	(0.474)	(0.022)	(0.222)	(0.013)	(0.053)	(0.154)	(0.18)	(0.045)	(0.009)
CIR	0.610***	-8.484**	-0.492***	9.019**	1.262***	-5.661***	-0.547***	-2.437***	3.198*	6.605***	-0.169	0.162**
	(0.013)	(3.773)	(0.054)	(4.021)	(0.300)	(0.369)	(0.177)	(0.352)	(1.652)	(2.412)	(0.168)	(0.071)
Threshold	25.638***	27.831***	25.652***	29.205***	22.901***	22.458***	22.951***	22.902***	24.691***	26.870***	9.218***	15.183***
	(0.108)	(0.018)	(0.053)	(0.059)	(0.475)	(1.255)	(2.564)	(0.728)	(0.236)	(1.155)	(0.318)	(0.653)
J-statistic	0.609	0.947	0.917	0.450	0.978	0.493	0.350	0.872	0.496	0.381	0.578	0.262
Upper Regime	0.238	0.192	0.447	0.168	0.277	0.251	0.269	0.276	0.041	0.098	0.69	0.333
Linearity test	0.054	0.072	0.034	0.000	0.000	0.056	0.000	0.005	0.042	0.000	0.000	0.051
Observations	36	36	36	36	81	81	81	81	198	198	198	198

China's Domestic Systemically Important Banks

We now move to examine the efficiency effect of diversification for China's domestic systemically important banks (D-SIBs). We can see that the empirical results for D-SIBs are similar to those for the whole sample. That is, with a lower level of diversification, the shift from traditional banking towards non-interest activities significantly increases the banks' risk level in terms of both idiosyncratic risk and the probability of default. However, the results show that once D-SIBs have exceeded a certain threshold point, they benefit from a significant risk reduction derived from an increase in income diversity and a shift from interest to non-interest income. The results for both idiosyncratic risk and financial distress are consistent at the 1% significance level.

Other Chinese Banks

The third column of Table 4.2 reports a different result compared with those for the other two sub-groups. Here again, it shows an inverse U-shape, where increased proportion of banks' non-lending business will lead initially to an increase in both idiosyncratic risk and banks' financial distress. However, after achieving a certain threshold point of diversification, N-SIBs will benefit from a reduction of risk.

The difference in results across the three groups could reflect the different size of banks, from large G-SIBs to medium-sized D-SIBs and smaller N-SIBs. For G-SIBs, the process of diversification can make banks more stable regardless of the level of diversification. However, our results for D-SIBs and N-SIBs echo the work of Gamra and Plihon (2011), who use data from both East-Asian and Latin-American markets and find that income diversification makes banks less stable in the early stages of engaging in mixed business lines, but that they become more stable with the expansion of non-interest activity. These differences can be explained by the fact that medium-sized D-SIBs and small-sized N-SIBs are still in the early stages of diversification with lower overall diversification level, combined with less accumulation of specialist expertise, weak risk management and unsound internal regulatory systems, and are thus ill-equipped to deal with riskier non-traditional businesses.

4.4.3 Components of Non-interest Income and Risk

Different components under the general heading of non-interest business may perform differently and, hence, may have different diversification effects (Stiroh and Rumble, 2006; Chiorazzo et al., 2008; Roy, 2015). Brunnermeier et al. (2012) suggest that trading and fee-based activities may have different risk implications, as trading activity is often accompanied by a greater increase in the variability in profits. In contrast, the fee-based activity is highly correlated with traditional business (Zhou, 2014), which would help the banks obtain superior information. This prompts us to explore the issue further by decomposing total operating income into three revenue classes and then investigate into the risk implications of each class. These components are fee and commission (Model 5), trading (Model 6), and other non-interest incomes (Model 7). Each of these three types of revenue is expressed as a share of total operating income. Regression results are reported in Table 4.3.

Such positive effects on banks' overall risk are mainly driven by the trading income. This result is in line with Estrella's (2001) finding that acquisition of securities firms would cause highly volatile returns in the US market. According to Boot and Ratnovski (2012), trading activity allocates too much spare capital to trading ex-post and takes away too many resources from traditional business. Therefore, such resources misallocation towards to trading business would raise banks' probability of failure. However, once a bank has exceeded the threshold level, all of those three activities will bring benefits due to risk reduction.

The second, third and fourth columns of Table 4.3 show the regression results for G-SIBs, D-SIBs and N-SIBs respectively. For all three groups, the trading and other non-interest activities exhibit an inverse U-shaped relationship with bank risk. We find that the risk for N-SIBs is more sensitive to the increase in trading activities in the early stage. At the same time, this group has the lowest threshold for trading activities. Hence, although the expansion of trading activities might cause more serious problems for N-SIBs in terms of financial distress, such activities will eventually help the banks to reduce their level of risk.

Table 4.3 Income diversification and risk for 35 Chinese banks, G-SIBs, D-SIBs and N-SIBs from 2007 to 2016

This table reports the first-differenced GMM threshold dynamic panel model developed by Seo and Shin (2016). Our dependent variable is insolvency risk using a accounting data based opposite Z-score. It-1 refers to the lagged one period of the dependent variables. COM is the ratio of net fee and commission income to total operating income; TRA is ratio of net trading income to total operating income; OTH is the ratio of net other operating income to total operating income. LCD is Loans / Customer Deposits, ETA refers to Equity / Total Assets, CIR is Cost to Income Ratio. J-statistic checks the null hypothesis, i.e., that the instruments used are not correlated with the residuals. Linearity test checks whether threshold exists. Figures in brackets present the standard error. ***, ** and * indicate significance at the 1%, 5% and 10% level.

	Whole Sample			G-SIBs			D-SIBs			N-SIBs		
	(5)	(6)	(7)	(5)	(6)	(7)	(5)	(6)	(7)	(5)	(6)	(7)
	Lower Regime											
It-1	-0.097	0.923***	1.364***	0.274	-0.415	-3.044	0.982***	2.701***	1.174***	2.834***	1.907***	1.779***
	(0.285)	(0.343)	(0.247)	(0.260)	(0.927)	(2.123)	(0.035)	(0.669)	(0.069)	(0.902)	(0.171)	(0.145)
COM	0.180			-0.082***			0.021			0.593**		
	(0.122)			(0.005)			(0.031)			(0.248)		
TRAD		3.138**			2.523***			2.158**			9.052***	
		(1.431)			(0.656)			(0.986)			(1.761)	
OTH			2.204**			2.545***			1.750***			1.858***
			(1.009)			(1.009)			(0.171)			(0.611)
LTA	-0.208***	-0.042	0.186**	0.056*	0.119*	0.831***	-0.011***	0.418**	0.024***	0.056	-0.016	-0.108***
	(0.051)	(0.100)	(0.090)	(0.033)	(0.064)	(0.355)	(0.004)	(0.189)	(0.008)	(0.076)	(0.018)	(0.014)
LCD	-0.085**	-0.048	-0.080*	-0.01	-0.004	-0.011	-0.247***	-0.129***	-0.216***	-0.036	0.036	-0.037*
	(0.036)	(0.042)	(0.048)	(0.019)	(0.054)	(0.025)	(0.068)	(0.026)	(0.008)	(0.031)	(0.026)	(0.019)
ETA	-0.277*	0.189	-1.779***	-0.982***	-0.263	-6.603**	-0.363***	1.829**	1.038***	-0.203	-1.256***	0.056
	(0.154)	(0.21)	(0.522)	(0.21)	(0.37)	(2.640)	(0.023)	(0.732)	(0.162)	(0.302)	(0.229)	(0.107)

Table 4.3 (continued)

						Upper Regime						
It-1	-0.605	0.672	1.627***	0.480	-0.180	-1.287	0.619***	3.555***	1.562***	2.535***	1.487***	1.394***
	(0.418)	(0.444)	(0.290)	(0.877)	(0.953)	(1.227)	(0.032)	(0.958)	(0.054)	(0.737)	(0.142)	(0.101)
COM	-0.461***			-0.148***			-0.154***			0.294		
	(0.118)			(0.041)			(0.009)			(0.231)		
TRAD		-0.299**			-0.340			-0.456			-0.098	
		(0.145)			(0.665)			(0.527)			(0.092)	
OTH			-1.325**			-0.842			-0.053***			-0.435***
			(0.550)			(0.879)			(0.013)			(0.121)
LTA	-0.164***	0.025	-0.064	-0.044	0.241***	0.181***	0.018***	0.130*	0.418***	0.023	-0.046***	-0.046**
	(0.041)	(0.066)	(0.048)	(0.228)	(0.073)	(0.068)	(0.005)	(0.071)	(0.112)	(0.054)	(0.014)	(0.019)
LCD	0.037	-0.035	-0.014	-0.012	-0.007	0.204	0.006**	0.160**	0.007	0.023	-0.009	-0.028
	(0.037)	(0.025)	(0.114)	(0.107)	(0.054)	(0.14)	(0.003)	(0.08)	(0.018)	(0.039)	(0.024)	(0.037)
ETA	-0.017	-0.319	0.551	-0.181	-1.380***	-2.174***	0.290***	2.354*	0.260	0.54***	-0.084	0.137
	(0.213)	(0.328)	(1.165)	(1.112)	(0.428)	(0.82)	(0.057)	(1.349)	(0.166)	(0.205)	(0.096)	(0.225)
Threshold	6.869***	0.437	0.633***	13.060***	0.670**	1.017***	10.322***	1.404***	0.631***	5.103***	0.340***	0.701***
	(0.563)	(0.426)	(0.200)	(0.174)	(0.284)	(0.076)	(0.260)	(0.014)	(0.052)	(1.188)	(0.059)	(0.179)
J-statistic	0.726	0.620	0.820	0.254	0.373	0.515	0.158	0.382	0.678	0.762	0.220	0.172
Upper Regime	0.423	0.630	0.369	0.292	0.504	0.464	0.364	0.205	0.478	0.403	0.698	0.289
Linearity test	0.001	0.065	0.000	0.093	0.032	0.095	0.051	0.623	0.036	0.062	0.079	0.000
Observations	315	315	315	36	36	36	81	81	81	198	198	198

Fee-based activities exert different effects on banks' overall risk level among the three groups. First, G-SIBs can always achieve benefits of risk reduction by increasing their fee-based activities. Moreover, when the proportion of fee and commissions achieves 13.06%, the coefficient changes from -0.082 to -0.148, indicating that the increase of such activity could play an accelerator role to reduce G-SIBs' risk and make these banks more and more stable. However, the results for D-SIBs are consistent with those for the whole sample, showing an inverse U-shape with the threshold at 10.322%. The regression results for N-SIBs indicate that banks in this group cannot obtain benefits from the expansion of fee and commissions in either the lower or upper regime.

The above result can be explained by the fact that G-SIBs have skills and expertise in fee-based activities, since most banks started getting involved in this kind of business in the 1990s, being followed later by D-SIBs and finally by N-SIBs. In the case of banks with well-established systems and skilled workers, the expansion of this business can provide continuing risk-reduction benefits.

Meanwhile, for D-SIBs, the sign for fee-based income in the lower regime changes from negative to positive. Thus there exists an inverse U-shaped relation between fee-based income and banks' risk indicator, with the threshold at 10.322%.

Next, for N-SIBs, although the expansion of fee-based income cannot reduce banks' risk in either the lower or upper regime, the coefficient changes from 0.593 with 1% significance level in the lower regime, to 0.294 with insignificant level in the upper regime. We suggest that this risk-enhancement result is mainly due to an internal problem whereby N-SIBs are more concerned with their interest business, while with regard to the non-traditional business they focus more on trading and other activities rather than on fee-based income: this group has the lowest level of average HHI (13.39) among the three groups (25.12 for G-SIBs and 18.92 for D-SIBs). Moreover, among all non-interest activities they focus mainly on more profitable and high-leverage trading and other non-interest activities, whereas they do not have sufficient ability to deal with the risk that is generated from this kind of non-traditional activity.

4.4.4 Income Diversification and Different Types of Risk

Having discussed effects of different components of non-traditional income on the overall risk of the banks, we now investigate how income diversification affects different types of risk. We follow Valverde and Fernández (2007) to decompose overall risk faced by Chinese banks into its three components, namely, credit, liquidity and interest rate risk. Table 4.4 presents the estimation results for the effects of diversification on each of these risks, i.e., on credit risk (Model 8), liquidity risk (Model 9) and interest rate risk (Model 10).

The first column of Table 4.4 reports the results for the whole sample; it shows the regression outcome when employing the proxy of credit risk as the dependent variable. We find that income diversification can always make banks riskier in terms of credit risk (CREDIT). Next, the results for the liquidity risk shown in Model 9 differ from those for credit risk, indicating that the liquidity risk (LIQUIDITY) is significantly negatively correlated with income diversification in both the lower and upper diversification regimes. Finally, Model 10 under the whole sample presents the estimation results in relation to interest rate risk (INTEREST) when it is specified as the dependent variable.

Turning to the next three columns, for G-SIBs, D-SIBs and N-SIBs respectively, we find a consistent result in terms of the liquidity risk, which implies that diversification brings benefits to banks' liquidity risk for both diversified and less diversified banks. This may be because, compared with traditional lending business, non-interest activities are less likely to be affected by the regulator's capital restrictions, such as the capital adequacy requirement. Rather, an increase in non-interest activities will provide liquidity for banks and, therefore, reduce bank liquidity risk.

Table 4.4 Income diversification and risk for 35 Chinese banks from 2007 to 2016

This table reports the first-differenced GMM threshold dynamic panel model developed by Seo and Shin (2016). Our dependent variables are loan default/total loans (CREDIT), liquidity assets/short term funding (LIQUIDITY), and interest rate risk calculated by interbank rate - interest rate for customer deposits; (INTEREST). It-1 refers to the lagged one period of the dependent variables. HHI indicates the income diversification using Herfindahl-Hirschman Index with the components of interest income and three activities under non-interest income. LCD is Loans / Customer Deposits, ETA refers to Equity / Total Assets, CIR is Cost to Income Ratio. J-statistic checks the null hypothesis, i.e., that the instruments used are not correlated with the residuals. Linearity test checks whether threshold exists. Figures in brackets present the standard error. ***, ** and * indicate significance at the 1%, 5% and 10% level.

	Whole Sample			G-SIBs			D-SIBs			N-SIBs		
	CREDIT	LIQUIDIT	INTERES	CREDIT	LIQUIDIT	INTERES	CREDIT	LIQUIDIT	INTERES	CREDIT	LIQUIDITY	INTERES
	Model 8	Model 9	Model 10	Model 8	Model 9	Model 10	Model 8	Model 9	Model 10	Model 8	Model 9	Model 10
	Lower Regime											
It-1	1.548**	1.370***	0.595***	-1.370***	0.399***	0.883***	0.319**	-0.095**	-1.229	-1.096***	1.532***	0.676
	(0.733)	(0.205)	(0.189)	(0.200)	(0.056)	(0.237)	(0.143)	(0.047)	(0.994)	(0.187)	(0.410)	(3.15)
HHI	0.100***	-0.685**	0.045	0.038***	-1.360***	-0.031***	0.034***	-0.627***	-0.245***	0.102***	-3.201***	0.305
	(0.024)	(0.337)	(0.030)	(0.004)	(0.096)	(0.006)	(0.005)	(0.14)	(0.035)	(0.022)	(0.906)	(0.437)
LTA	0.064*	-0.204	-0.109***	0.308***	-0.198**	0.004	-0.005	0.258	0.187***	0.076***	-0.769	-0.214**
	(0.038)	(0.603)	(0.015)	(0.028)	(0.085)	(0.033)	(0.003)	(0.173)	(0.017)	(0.011)	(1.05)	(0.105)
LCD	-0.063***	-1.742***	-0.059***	0.133***	-0.913***	-0.028	0.020***	-1.450***	0.042***	-0.031***	-0.198	0.017
	(0.02)	(0.587)	(0.013)	(0.016)	(0.073)	(0.019)	(0.002)	(0.113)	(0.012)	(0.010)	(0.62)	(0.108)
ETA	-0.399**	3.540**	0.03	-2.325***	0.806*	-0.500**	-0.266***	3.386***	-0.340**	-0.245***	2.270	0.756*
	(0.200)	(1.682)	(0.051)	(0.177)	(0.481)	(0.207)	(0.051)	(0.701)	(0.151)	(0.062)	(1.937)	(0.447)

Table 4.4 (continued)

	Upper Regime											
It-1	-0.072	-0.230	-0.146	-0.719***	-1.927***	-0.056***	-0.539***	-0.103***	0.574	-0.322*	0.501**	0.252***
	(0.257)	(0.324)	(0.141)	(0.083)	(0.182)	(0.021)	(0.170)	(0.036)	(0.516)	(0.168)	(0.239)	(0.09)
HHI	0.057***	-1.072**	-0.047***	-0.214***	-0.251***	-0.108***	-0.006**	-1.234***	-0.077**	0.032***	-0.320	-0.044***
	(0.01)	(0.451)	(0.011)	(0.019)	(0.004)	(0.004)	(0.003)	(0.059)	(0.032)	(0.004)	(0.575)	(0.007)
LTA	-0.030***	-0.399	-0.066***	0.225***	0.007	0.125***	-0.019***	0.497***	0.090***	0.022***	-0.907**	-0.042***
	(0.006)	(0.336)	(0.01)	(0.013)	(0.028)	(0.005)	(0.003)	(0.069)	(0.01)	(0.006)	(0.431)	(0.006)
LCD	0.039**	0.747	-0.059***	-0.040***	0.038	-0.039***	0.009	0.595***	0.038	0.082***	-1.054***	-0.034***
	(0.016)	(1.289)	(0.013)	(0.001)	(0.031)	(0.001)	(0.005)	(0.115)	(0.032)	(0.011)	(0.32)	(0.009)
ETA	0.03	0.29	-0.177**	-0.448***	-3.624***	-0.563***	0.210***	-8.589***	0.002	-0.218***	6.859***	-0.298**
	(0.067)	(1.96)	(0.073)	(0.019)	(0.104)	(0.024)	(0.042)	(2.231)	(0.284)	(0.042)	(2.062)	(0.121)
Threshold	14.996***	20.560***	17.442***	25.922***	26.939***	25.658***	26.913***	21.098***	25.682***	14.579***	12.961***	6.265***
	(0.813)	(1.953)	(0.671)	(0.047)	(0.061)	(0.089)	(0.334)	(0.324)	(1.549)	(0.660)	(0.929)	(0.455)
J-statistic	0.102	0.229	1	0.971	0.986	0.986	0.702	0.995	0.521	0.452	1	0.821
Upper Regime	0.505	0.269	0.403	0.403	0.344	0.442	0.145	0.343	0.188	0.376	0.466	0.873
Linearity	0.095	0.004	0.084	0.000	0.046	0.000	0.033	0.007	0.067	0.000	0.000	0.097
Observations	315	315	315	36	36	36	81	81	81	198	198	198

However, the regression results for credit and interest rate risks vary among the three groups. In detail, for both G-SIBs and D-SIBs, we see that there is an inversion of the signs for the diversification effect on credit risk between the low and high diversification regimes. At lower levels of diversification, income diversification will generate more credit risk. Once a bank has passed the threshold level, the increase of non-interest income will then lead to a reduction of credit risk. However, 59.7% of observations for G-SIBs, and 85.5% for D-SIBs, are in the lower diversification regime. Therefore, currently, most Chinese systemically important banks are suffering an increase in credit risk as a result of their relatively low level of diversification.

However, the result for N-SIBs is different. In both the lower and upper regimes, the expansion of non-interest activities does not reduce banks' credit risk at all. This result is also consistent with our previous results in section 4.4.2, as the credit risk is mainly created from traditional lending and fee-based activities, which are highly correlated with the interest income. Such low ability to deal with fee-based income and its risks leads to the enhancement of credit risk from income diversification.

With regard to interest risk, for G-SIBs and D-SIBs we find a consistent result, where similar to the situation with liquidity risk, in both the lower and upper regimes diversification can reduce interest risk. One plausible explanation for this is that banks' exposure to changes in interest rates is the result of bank asset-liability management.

A change in the interest rate would directly affect banks' interest income and their liabilities; in particular, an increase in the interest rate would largely reduce the interest margin and the banks' equity capital. Therefore, by engaging in non-interest activities banks can reduce their exposure to interest rate risk, especially when compared with banks that have a large percentage of mortgage lending business (Delong, 2001).

For N-SIBs, which tend to be less diversified, an increase in the diversification level can increase the banks' exposure to interest rate risk. Then, after passing a low threshold level (6.265), this correlation becomes negative. We suggest that this result is because the overall diversification level for N-SIBs is still relatively low, where the proportion of non-interest income occupies only 7.29% of total operating income. Hence, in the early stages of diversification, the increase of non-interest income will not have a big effect on banks' overall interest risk.

4.5 Conclusion

This chapter examines to what extent income diversification affects the risks of Chinese banks. The majority of previous studies indicate a linear relation between income diversification and risk, finding either a negative correlation that suggests banks should diversify, or a positive correlation that suggests banks should remain focused on core business. However, by adopting the first-differenced GMM estimator for the dynamic threshold panel data model, we get results showing that in the case of

Chinese systemically important banks, the relation between income diversification and risk is not linear, and the effects of diversification vary with different sources of non-interest activities and different measures of risk.

Generally, there exists an inverse U-shaped relation between diversification level and risk in the Chinese banking industry. Income diversification will reduce bank risk only after the bank has passed a certain threshold of income diversification. This pattern of relationship seems to be driven mainly by the learn-by-doing effect and the mitigation of agency problems, which result from the expansion of non-interest activities. After dividing the sample into three groups based on the BIS definition and the Chinese regulator's classification, we find that, for G-SIBs, diversification has a significant negative effect on both banks' idiosyncratic risk and banks' financial distress. However, for D-SIBs and N-SIBs, the effects again exhibit an inverse U-shape, where in the early stages of income diversification banks incur a discount and become less stable, while they become more stable after achieving a certain threshold point of diversification. We suggest that these differences are due to different diversification strategies and risk preferences, which lead to different income structures.

The diversification effect on bank risk turns out to be not uniform across different business lines. Where there is only a low level of diversification, both trading and other non-interest activities will lead to increased exposure to risk; only once the bank has achieved a certain diversification level will these activities start to provide diversification benefits that will lower bank risk. With regard to the different components of non-interest business, fee and commissions activities will decrease bank risk for G-SIBs and increase risk for N-SIBs regardless of diversification level, while for D-SIBs there is an inverse result, positive for banks with a lower level of diversification and negative for more diversified banks.

We also examine the diversification effect across different types of risk. Evidence suggests that for G-SIBs and D-SIBs diversification can reduce credit risks only when the banks have passed a certain threshold point, while for N-SIBs diversification cannot bring any improvement for credit risk regardless of diversification level. Similarly, the interest rate risk will be reduced only for highly diversified G-SIBs and D-SIBs. Finally, diversification will always reduce the liquidity risk, for all three groups. However, the reduction of the liquidity risk cannot fully offset the enhancement of the credit and interest rate risks. Therefore, it is necessary for banks to cross the threshold in order to obtain the risk-reduction benefits from diversification. Furthermore, this implies that to fully reap the benefits of risk reduction from income diversification, banks need to accumulate sufficient banking human capital and to establish an effective supervision system.

Chapter 5

Chapter 5 Income Diversification and Bank Efficiency

This chapter examines the efficiency of the Chinese banking sector in relation to banks' diversification operations. In a two-step approach, the chapter first calculates both cost and profit efficiency scores via stochastic frontier analysis using the method of within maximum likelihood estimation (WMLE). Then, the investigation employs a dynamic Tobit model in order to shed light on the diversification-efficiency nexus in the Chinese banking market.

Chapter 5

Income Diversification and Bank Efficiency

Chapters 3 and 4 have explored the benefits and risks associated with Chinese banks' engagement in income diversification. Another critical aspect of the effects of banks' income diversification is the extent to which banks' efficiency would be affected. Therefore, in order to provide a fuller picture of the consequences of banks' diversification, this chapter is devoted to investigating the efficiency of the diversifying banks in China. In a two-step approach, first, bank efficiency scores, both cost and profit, are calculated for the three main categories of Chinese banks. The computation is based on stochastic frontier analysis using within maximum likelihood estimation (WMLE). In the second step, a dynamic Tobit model is estimated to examine unobserved, time-invariant bank heterogeneity. Finally, the empirical findings are discussed with reference to the different banking groups.

5.1 Introduction

The impact of diversification on bank efficiency has been a contentious issue in the literature. One school in the debate subscribes to the view that diversification is efficiency enhancing. Based on the portfolio theory, Meng et al. (2017) argue that diversification can yield separation of risks and hence is beneficial to banks' efficiency. Additional channels through which diversification may enhance banks' efficiency include gains accruing due to scale and scope economies (Meslier et al., 2014), tax reduction as a result of higher financial leverage (Elsas et al., 2010), improved corporate governance (Lin et al., 2012), and a reduction in asymmetric information between borrowers and lenders (Akhigbe and Stevenson, 2010).

On the other hand, the opposing school argues that shifting from focused to diversified operations has a negative impact on bank efficiency. This may be caused by, for example, the increased correlation of internal businesses and the growing complexity across business lines (Elyasiani and Wang, 2012), where the presence of too many business lines may lead to disorganized management. Hence, more diversified banks can incur additional overhead costs (Elsas et al., 2010), inefficient cross-subsidization (Klein and Saidenberg, 2010), inefficient internal capital markets within multinational groups (Curi et al., 2015), and the problems related to 'too big to fail' status (Quaglia and Spendzharova, 2017). Furthermore, diversification can cause banks to have no power or incentive to monitor (Allen et al., 2011; Adzobu et al., 2017).

Ultimately, whether or not diversification can increase or reduce bank efficiency is a matter of empirical evidence. This chapter contributes to the debate through empirical investigation into the efficiency effect of diversification in the Chinese banking sector. As in previous chapters, the sample comprises 40 major Chinese commercial banks, which are divided into three sub-groups: Global Systemically Important Banks (G-SIBs), Domestic Systemically Important Banks (D-SIBs), and banks that are not classified by the authorities as systemically important (N-SIBs). This grouping enables us to examine the possible heterogeneity of efficiency effects due to bank diversification.

Similar research in the previous literature is mostly based on analysis of financial ratios, and employs balance sheet and stock market data (e.g. Stiroh and Rumble, 2006; Demirgüç-Kunt and Huizinga, 2010; Meslier et al., 2014). However, financial ratios suffer from several accounting biases, such that they are unlikely to offer a full account of the business mix and input prices (Titova, 2016) and fail to provide information about managerial actions (Yeboah and Asirifi, 2016) or the quality of service under complex business networks (LaPlante, 2015).

We deploy a two-stage approach in which the first step is to obtain the efficiency scores through the stochastic frontier analysis. Based on within maximum likelihood estimation (WMLE), as developed by Chen et al. (2014), stochastic frontier analysis

(SFA) contains more information and more factors, which are difficult to quantify when using financial ratio based estimation and non-parametric approaches, such as data envelopment analysis (DEA). Furthermore, the SFA method employed by this research is particularly appropriate for the Chinese context, since issues regarding data availability mean that the panel data are relatively short. My approach to SAF analysis, which employs the first-difference data transformation, eliminates nuisance parameters, thus solving the incidental parameters problem and making the estimation of the efficiency scores unbiased (Greene, 2005).

In the next stage, we deploy the dynamic Tobit model to determine to what extent diversification drives Chinese banks' efficiency. Unlike OLS and other linear estimation methods, the Tobit model is able to take into account the censored nature of the dependent variable. Since in the model in this study the efficiency scores are limited to between 0 and 1, the Tobit model is suitable for use in the regression on these variables and should yield consistent estimates that avoid the problems of bias and inconsistency associated with OLS (Souza and Gomes, 2015). The dependent variable used in the regression is assumed to be half normally distributed; hence, the regression errors are subject to normal distribution. Most non-censored estimates, such as OLS, assume that the dependent variable can take on every negative or positive real number. This means ignoring fractionality, which may lead to biased estimation and inconsistent parameters (Greene, 1980). In addition, other non-linear estimations, such as the fractional Probit model, are less likely to capture the dynamic effect. The presence of lagged dependent variables requires specification of the distribution of unobserved effects in a maximum likelihood framework, which leads to inconsistent results in the fractional Probit model (Papke and Wooldridge, 2008).

We apply the dynamic doubly censored Tobit model with a left censored bound of zero and a right censored bound of one to regress efficiency scores against banks' income diversification (Elsas and Florysiak, 2015). Several control variables are introduced into the model. This modelling choice allows for bank heterogeneity, does not require balanced panel data and is robust to missing data in unbalanced panels.

Our study is also the first to investigate the diversification effect on banks' efficiency across banking groups. This yields a number of insights, as banks in the three groups exhibit very different characteristics in terms of capital restriction, size and diversification level, which could help to shed light on, for example, whether the diversification effect varies with bank scale.

The remainder of the chapter is organized as follows. Section 5.2 provides an overview of the relevant literature regarding bank efficiency and income diversification. The variables, data, and methodology are discussed in Section 5.3. Section 5.4 outlines the model specification and reports the empirical results. The conclusion is presented in Section 5.5.

5.2 Literature Review

Two main theoretical views regarding the effect of diversification on banks' efficiency have emerged in the literature, namely, the bank-based view and the market-based view. Built on the theory of financial intermediation, the bank-based view maintains that the benefits generated by diversification stem mainly from the information advantages (Bencivenga and Smith, 1991; Saunders and Walter, 1994; Lepetit et al., 2008; Elyasiani and Wang, 2012). According to Elyasiani and Wang (2012), information can be treated as an important input factor to influence banks' efficiency in terms of customer relation consolidation and credit screening. Alternatively, with mixed business lines, managers are more likely to lower their personal risk by over-diversifying their banks' portfolios (Deng and Elyasiani, 2008). As a result, non-interest income could result in excessive profits and bonuses to managers themselves. In this situation, banks would continually expand the range of non-traditional business, even if diversification of activities lowers the market valuation of the banking conglomerate (Demirgüç-Kunt and Huizinga, 2010).

While banks can reap diversification benefits through operational synergies (Lin, 2012), the attainment of these synergies relies on scale economies (Stiroh, 2000; Sanya and Wolfe, 2011). As argued by Drucker and Puri (2008) and Klein and Saidenberg (2010), the expansion of non-interest business is largely based on banks' infrastructure, and a mixed business line strategy could help banks spread fixed costs and managerial overheads. Scale economies may also lead to operational benefits because cross-selling strategy companies could share the costs of monitoring, advertising and account maintenance, thus further reducing cost and hence improving banks' production efficiency (Elyasiani and Wang, 2012).

From the perspective of resource allocation, whereas focused-business companies can only configure resources through external capital markets, diversified companies can be more effective through the internal capital market (Elyasiani et al., 2016). This could help banks to reallocate internal resources from less-profitable sectors to more-effective sectors.

The market-based view introduces a competitive framework to explain how income diversification could result in efficiency improvement or discount. Several studies suggest that the diversification process could lead to more intense competition in the banking industry (e.g. Schaeck and Cihak, 2010; Ariss, 2010; Ibragimov et al., 2011; Beck et al., 2013). Authors such as Lepetit et al. (2008), Schaeck and Cihak (2010), Allen et al. (2011), Dell'Ariccia et al. (2012) and Amidu and Wolfe (2013) then believe that a more intense competitive environment could help banks achieve more efficient management of operation and risk.

Conversely, some researchers argue that fiercer competition could exacerbate risk. Vives (2011) suggests two channels for such risk enhancement. First, increased interbank competition could exacerbate the coordination problem and hence increase banks' frangibility. Second, managers' risk-taking behaviour may change in the face of a more competitive environment. With more pressure on profits, there would be an increased incentive for managers to take on more excessive risk on either side of the bank's balance sheet, resulting in higher fragility (Amidu and Wolfe, 2013). In addition, in a more-competitive banking market banks earn less informational rent from their relationship with borrowers and would therefore have less incentive to properly screen borrowers, which would further increase the risk of fragility (Allen and Gale, 2004; Beck et al., 2013).

In empirical studies, bank efficiency can be evaluated through ratio analysis that employs accounting data (Cornett et al., 2006; Xu, 2011; Jiang et al., 2013; Sun et al., 2013). However, accounting ratios are unlikely to offer a full account of the business mix and input prices (Havranek et al., 2016) because accounting-based efficiency measurements implicitly assume that all assets are equally costly to produce and that all locations have equal operation expenditures.

Alternatively, data envelopment analysis (DEA) has been widely used in the literature for estimating bank efficiency (i.e. Biener et al., 2016; Aggelopoulos and Georgopoulos, 2017). DEA is a non-parametric tool for performance evaluation and benchmarking. The method empirically measures efficiency of decision-making units by estimating the efficiency frontiers, and can also be used for benchmarking in operations management. Since its introduction by Charnes et al. (1978), DEA has been applied to many industries, including the banking sector. In DEA, the efficiency is measured against the highest observed performance instead of an average (Hjalmarsson and Veiderpass, 1992). As a non-parametric approach to measuring efficiency, the major advantage of DEA is that it does not assume a particular functional form/shape for the frontier; hence, it can be used when conventional cost and profit cannot be justified (Berger and Humphrey, 1997). However, its drawbacks include a lack of measurement of errors and luck factors, sensitivity to outliers, an inability to measure absolute efficiency, and ignoring price information (Berger and Mester, 1997; Fiorentino et al., 2006).

More recently, researchers have increasingly used stochastic frontier analysis (SFA) to evaluate banks' efficiency. SFA is a fully parameterized model and is now the mainstream parametric technique for efficiency analysis. Compared with non-parametric methods, such as DEA, stochastic methods could be more effective and robust when treating noisy data (LaPlante, 2015). Due to consideration of random errors in the functional form, they can measure some factors that are very difficult to quantify, such as companies' luck or even the influence of the weather.

Originally developed by Aigner et al. (1977) and Meeusen and Van den Broeck (1977), SFA has been applied in a large number of efficiency studies, including studies of banks; see Berger and Humphrey (1997) for an extensive survey of 130 studies regarding the efficiency in financial institutions. Many varieties of the stochastic frontier model have appeared in the literature; see a major survey by Kumbhakar and Lovell (2003) and also Bauer (1990) and Greene (2008). The method involves estimation of both cost and profit efficiency (Kumbhakar and Lovell, 2003). With regard to cost efficiency, SFA measures how far a firm is from full-cost minimization. In the profit efficiency analysis, the firm in question is treated as a profit-maximizer. Since the concept of profit efficiency takes into consideration the effects of output choice on costs and revenues, it is broader than that of cost efficiency.

The empirical evidence regarding the effects of bank income diversification on efficiency has been mixed. Pasiouras et al. (2007) suggests that there is a positive effect on banks' efficiency level. Such improvement in banks' efficiency could be explained by the soft information provided through prolonged close interaction with clients (Gourlay et al., 2006). Doan et al. (2017) focuses on a cross-country case and suggests that banks can achieve significant profit efficiency gains through greater diversification of their risk exposure. In addition, a better mix of financial products also protects banks' firm-specific human capital, as diversification through mergers and acquisition will help banks to expand the skill set of managers, which will in turn contribute to improving risk management and smoothing credit operations.

Beccalli and Frantz (2009) employ SFA to generate estimates of cost and alternative profit efficiencies from 1991 to 2005. They find a marked improvement in cost efficiency and argue that this improvement would not have occurred in the absence of increases in both on- and off-balance sheet activities in EU mergers and acquisitions. Similar results are obtained by Doan et al. (2017), who, by adopting cross-country data, demonstrate that increased diversification tends to improve bank efficiency.

Among the research on emerging markets, Kwan (2006) analyses the cost efficiency of Hong Kong banks; by employing SFA, he verifies that efficiency improvement is mainly generated from scale economies because of the increased contribution of non-interest income. Alhassan (2015) uses the same parametric approach to estimate both cost and profit efficiency of banks in Ghana, and detects efficiency improvement.

However, some studies provide evidence for a diversification discount. The results of Wu's (2008) investigation of 11 Taiwan banks suggest that an expansion of broad financial product lines would not bring an efficiency improvement but would further increase the losses from bad loans and erode banks' original efficiency level. Similarly, Abbott et al. (2013), in their study of Australian banks over the period 1983-2001, observe that an increase in the number of business lines through diversified growth does not drive significant improvement in banks' overall efficiency. In particular, banks in the very early stages of diversification and business expansion through mergers with other financial institutions might not achieve competitive advantages in the short term as they lack relevant competence. Several studies support this view (e.g. Barth et al., 2013; Alhassan and Tetteh, 2017), confirming that for banks, especially in the early stages of diversification, lack of experience causes inefficiency. This would be especially so in the case of emerging countries.

Research has also found that bank size is relevant to the effect of income diversification on efficiency. Empirical evidence from the US and Europe markets, which accounts for the bulk of the current research in the field, generally suggests that an increase in non-interest activities can improve efficiency through economies of scale (Drake et al., 2009; Elsas et al., 2010), which implies that the benefits of income diversification are driven by a larger bank size. In contrast, small banks emphasize basic banking activities with low-cost funds and high-quality investments, thus limiting their overall performance and efficiency. Further, evidence indicates that once companies have achieved a certain scale, then diminishing profitability and productivity would stimulate them to search for new investment opportunities (Bakke and Gu, 2017). Therefore, a diversification strategy is more likely to be adopted by larger companies with diminishing value.

However, using a sample of Ukraine banks, Mertens and Urga (2001) find that small commercial banks have more efficient performance in terms of cost compared with large-sized banks, and thus detect diseconomies of scale in the banking sector. Similarly, in their investigation of the US bank holding companies, Akhigbe and Stevenson (2010) find that the benefits from scale economies are not sufficient to improve banks' efficiency, but generate an efficiency discount.

Research that examines the effect of income diversification on Chinese banks is just emerging. Zhang (2003) investigates Chinese listed commercial banks and finds that banks' profitability is highly correlated with diversification levels, with a positive sign.

Meanwhile, banks' operational risk has a non-significant but negative correlation with diversification. Xia and Huang (2017) further suggest that the risk-reduction effect is mainly generated from portfolio diversification.

Chi et al. (2006) apply DEA to balance sheet data from 14 Chinese banks and find that more diversified banks with higher levels of non-interest activities could gain large improvements in their efficiency scores. Using the same efficiency estimation approach as Chi et al. (2006), Chen and Chen (2015) expand the sample to city banks in China and find a diversification premium, driven mainly by the accumulation of professionals and technological spillover effects from other business lines.

Wei and Liu (2007) introduce the entropy index to evaluate the diversification level in the Chinese banking sector and find a very small positive diversification effect on banks' efficiency. Xia and Huang (2017) detect a less-significant efficiency premium and present evidence that the increased management and operational costs greatly decrease the efficiency improvement obtained from a cross-selling strategy. Similar results are reported in Liu and Ji's (2014) study of 45 Chinese banks during the period from 2008 to 2012. By employing the DEA approach, Liu and Ji (2014) find that the expansion of non-interest activities causes devaluation of banks' efficiency, driven mainly by risk enhancement and increased management cost.

5.3 Variables, Data and Methodology

5.3.1 Variables

Measures of Banks' Efficiency. Two efficiency scores are used in this chapter, namely scores for cost efficiency and for profit efficiency. Both are calculated through stochastic frontier analysis (SFA) deploying the within maximum likelihood estimation (WMLE) method. Each efficiency score ranges from 0 to 1, indicating least to highest efficiency. A commercial bank with an efficiency score of 0.7 is 70% as efficient as the best-performing banks in the sample year.

The banking literature includes two main perspectives on the role of commercial banks and the components of inputs and outputs used to estimate efficiency score. The production approach suggests that production units use physical inputs such as capital and labour to supply service to customers to achieve outputs such as taking customer deposits and issuing loans. On the other hand, the intermediation approach treats commercial banks as intermediaries, whose function is to gather funds from the public and transfer these into profitable assets and projects. Owing to issues regarding data availability, this study follows Dong et al. (2016) in choosing the intermediation approach to estimate the efficiency level. This is because the information required under the production approach, such as the number of accounts held by the bank, is not publicly available, whereas the intermediation approach requires accounting-based information that can be found in public annual banking reports.

Therefore, this thesis uses two inputs (x_{it}) prices, namely the price of total physical capital (TC), which is measured by the ratio of other operating expenses to the book value of fixed assets; and the price of total borrowed funds (TF), which is measured by the ratio of total interest expenses on borrowed funds to total borrowed funds. The outputs (y_{it}) can be broken down into total loans (TL), other earning assets (OEA), and non-interest income (LA). The total cost used in the model includes both interest and operating expenses, including interest expenses, employee benefits, employee salaries and other operating costs.

To solve the omitted variables problem of the sample of banks, this study introduces three control variables. Following Dong et al. (2014), we use the total equity capital (z) of the specific banks as a quasi-fixed input in the banking cost function in order to control for banks' insolvency risk and different risk preferences. In addition, time trend (T) is used to account for the effects of technical progress, such as the learning-by-doing effect and technical spillover, over time.

Measures of Income Diversification. Following Amidu and Wolfe (2013), Gurbuz et al. (2013) and Meslier et al. (2014), we adopt the Herfindahl–Hirschman index (HHI) as the indicator of diversification. It is commonly used in similar research and is calculated as:

$$DIV = 1 - [(INT / TOR)^2 + (FEE / TOR)^2 + (TRA / TOR)^2 + (OTH / TOR)^2] \qquad (5.1)$$

where INT is the gross interest revenue, TOR is the total operating revenue, COM refers to the ratio of net fee and commission income to total operating income, TRA is the ratio of net trading income to total operating income, and OTH indicates the ratio of net other operating income to total operating income.

The investigation of diversification activity considers three types of income, namely, fee and commission income, trading income and other income. Following Köhler (2014), we use the corresponding indexes as proxies. These are the ratio of net fee and commission income to total operating income (COM), ratio of net trading income to total operating income (TRA), and ratio of net other operating income to total operating income (OTH).

Measures of Competitiveness. The Lerner index is adopted as the indicator of the level of competitiveness of the banking sector. The Lerner index is defined as the difference between a bank's price and the marginal cost divided by the price. The price is estimated by the average price of bank production as the ratio of total revenue to total assets (Tan et al., 2017), that is:

$$\text{Lerner} = (\text{p} - \text{MC})/\text{p} \tag{5.2}$$

The higher the index is, the more market power and competitiveness the bank in question possesses. The marginal cost is the key input for estimating the Lerner index, and it can be calculated by taking the first derivative of the dependent variables in the translog equation. Specifically, following Tan et al. (2017), the marginal cost is estimated on the basis of a translog cost function with signal output (total assets). Because of the data restriction of the labour process, we select two input prices, namely price of capital and price of funds. Also, we use a fixed net-put (equity) and technical changes (using a time trend as a proxy).

Other Variables. The other variables include the following:

NIM: This is the net interest margin, indicating the net interest revenue over total earning assets. It is intended to describe the interest-based activities (Lepetit et al., 2008; Busch and Kick, 2009; Köhler, 2014).

ETA: To adjust for banks' attitude toward efficiency, we adopt the ratio of equity to assets, which describes the degree of total financial leverage and capital adequacy (Stiroh, 2004; Pennathur et al., 2012; Gurbuz et al., 2013).

CIR: The cost-income ratio is estimated through the operating expenses relative to gross income, which measures banks' cost structure (Busch and Kick, 2009).

5.3.2 Data Sample

Our sample comprises an unbalanced panel of 40 Chinese commercial banks from 2005 to 2016, with annual data drawn mainly from BankScope and banks' annual reports. The sample accounts for 79% of total assets of the Chinese banking industry. Drawing from Basel III and the China Banking Regulatory Commission (CBRC), the banks are divided into three groups: global systemically important banks (G-SIBs), domestic systemically important banks (D-SIBs), and other banks that are not classified by the authorities as systemically important (N-SIBs).

5.3.3 Methodology

5.3.3.1 Investigation Strategy: Estimation of the Efficiency Scores

We adopt a two-stage strategy to investigate the relationship between bank efficiency and bank diversification in China. First, we estimate the efficiency of the banks. This is achieved by using stochastic frontier analysis (SFA) to evaluate banks' efficiency scores. Employing a set of statistical techniques for economic modelling of firm behaviour, the SFA explicitly recognizes the existence of firm inefficiency. Its theoretical underpinning can be traced back to Hicks (1935), who claimed that in addition to seeking profit maximization, monopolists may have other motivations that lead to sub-optimality of production. This argumentation has opened a path for research on producers who behave in a less than optimal manner when seeking profit maximization or cost minimization. Aigner et al. (1977) and Meeusen and Van den Broeck (1977) were among the first to apply the theory to empirical estimation of producers' conduct in the presence of firm inefficiency. The empirical research was initially focused on the production function, and then expanded to the cost function. Subsequently, the research has extended from economics to financial studies (Berger and Humphrey, 1997; Kumbhakar and Lovell, 2003; Cavallo and Rossi, 2002; Kraft et al., 2006; Fenn et al., 2008; Kao and Liu, 2009; Feng and Zhang, 2012; Dong et al., 2014; Dong et al., 2016).

For illustration, we start with the production frontier model, which is the empirical departure point for SFA. The production frontier model in log form can be presented as:

$$y_{it} = \alpha_i + \beta^{`} x_{it} + \varepsilon_{it}, \tag{5.3}$$

$$\varepsilon_{it} = \nu_{it} - u_{it}.$$

where i = 1, . . . , N indexes firms and t = 1, . . . , T indexes time periods. In Eq (5.3), y_{it} is the observed scalar output of the producer i at time t; x_{it} represents the vector of N production inputs used by producer i (e.g. labour and capital); β is a vector of technology parameters to be estimated, so that f(x_{it}, β) is known as the production frontier since it indicates the frontier of maximal output for a given set of inputs x_i. In addition, $\alpha_i$captures the unobserved heterogeneity in terms of time-invariant effects (of incidental parameters), and ε_{it} indicates the error term. This error term is a compound one consisting of two components: v_{it} $and - u_{it}$. Here, $\{v_{it}\}$ is the noise component capturing the effects of random shocks affecting the production process. This component introduces stochasticity into the model. The {- u_{it}} component contains non-negative errors representing unobserved inefficiency, which is the salient feature of SFA. To elaborate, let TE_i denote the i-th firm's technical efficiency, measured by the ratio of observed output to maximum feasible output. TE_i = 1 means firm i obtains the maximum feasible output, while TE_i < 1 indicates that the firm achieves less than its maximum feasible output. So, we have $TE_i \leqslant 1$. Further, if we let $TE_i = -u_i$, then in exponential form, we have exp TE_i= exp $\{-u_i\}$, where $u_i \geq 0$, given $TE_i \leq 1$. Plugging exp $\{-u_i\}$ into Eq. (5.1), and recall that it is in log form, we have:

$$y_{it} = \alpha_i + \beta^{`} x_{it} + v_{it} - u_{it} \tag{5.4}$$

This sheds further light on Eq. (5.3), showing that Eq. (5.4) is actually an error-component model.

Whereas we employ the production frontier model for illustration of the modelling setup and methodology, SFA also examines cost efficiency (Kumbhakar and Lovell, 2003) and has been applied to other areas of economics and banking analysis. For functional forms, in addition to the common use of natural logarithms, other forms such as translog functions are also modelled. Depending on the modelling specification, appropriate elements are selected for the cost or profit frontier of x_i. The (u_i) component of the composed error can also be production, revenue, profit, or cost inefficiency.

Given that the research interest of this chapter is bank efficiency in China, we specify stochastic frontier analysis in terms of both profit and cost efficiency (See Eqs. 5.28 – 5.31). The underlying model is similar to that of the production frontier model. Some revisions are made so that the examination addresses both the profit frontier and the cost frontier function. In these models, it is the banks rather than corporate producers that are the profit-maximizers or cost-minimizers. The outputs are the observed total cost or profits of the bank i at time t.

Estimation of SFA may be conducted via Greene's (2005) true fixed-effects approach. However, that approach suffers from the incidental parameters problem, whereby the variance parameters are more likely to be affected under the short-panel condition (Greene, 2005). Belotti and Ilardi (2012) suggest that this may be improved if the panel length is sufficiently large, 15 or greater. However, since the number of time periods in the data sample is only 12, Greene's model is not suitable for the estimation, due to the limited data. Instead, we adopt the method of within maximum likelihood estimation (WMLE) introduced by Chen et al. (2014) based on fixed-effects estimation. More specifically, Chen et al.'s (2014) estimation is based on the within-transformed model using the maximum likelihood method. This procedure does not suffer from the 'incidental parameters' problem because within-transformation removes the incidental parameters and the firm effects are fixed, such that:

$$\tilde{z}_{it} = z_{it} - \bar{z}_i \tag{5.5}$$

where for each panel i and any variable (z), the individual mean ($\bar{z}_i$) is subtracted from the observed value in period t (z_{it}) which can be defined as $\bar{z}_i = \frac{1}{T}\sum_t z_{it}$.Therefore, deviations from the means ($\tilde{z}_{it}$) can be used in the model. The resulting formulation is free of α_i; specifically, $\tilde{\alpha}_i = 0$. Thus, the fixed-effects stochastic frontier model with within transformation is of the form:

$$\tilde{y}_{it} = \beta^{`}\tilde{x}_{it} + \tilde{\varepsilon}_{it}, \tag{5.6}$$

$$\tilde{\varepsilon}_{it} = \tilde{v}_{it} - \tilde{u}_{it}, \tag{5.7}$$

$$\nu_{it} \sim IID \;\; \mathcal{N}(0, \sigma_v^2), \tag{5.8}$$

$$u_{it} \sim IID \;\; \mathcal{F}_\mathrm{u}(\sigma_u^2), \mathrm{i} = 1, \ldots, \mathrm{n}, \mathrm{t} = 1 \ldots, \mathrm{T}, \tag{5.9}$$

where error term ε_{it} indicates the difference between the idiosyncratic error term ν_{it} and inefficiency component u_{it}. ν_{it} and u_{it} are independently distributed. The inefficiency term u_{it} is distributed according to $\mathcal{F}_\mathrm{u}$ with a specific non-normal distribution, and we assume that it is half-normal, whereas ν_{it} is normally distributed. Let $\lambda = \frac{\sigma_u}{\sigma_v}$ and $\sigma^2 = \sigma_u^2 + \sigma_v^2$. Then, the density of the composed error should be:

$$\mathrm{f}(\varepsilon) = \frac{2}{\sigma} \varphi\left(\frac{\varepsilon}{\sigma}\right) \phi\left(-\frac{\lambda\varepsilon}{\sigma}\right) \tag{5.10}$$

The distribution of equation (5.10) is a member of the skewed normal family introduced by Azzalini (1985), which suggests that the Closed Skew Normal (CSN) distribution is suitable in the stochastic frontier context. The distribution of the composed error can be written as:

$$\epsilon_{it} \sim CSN_{1,1}(0, \sigma^2, -\frac{\lambda}{\sigma}, 0, 1) \tag{5.11}$$

The density of $CSN_{p,q}$ distribution includes a p-dimensional pdf and a q-dimensional cdf of a normal distribution. With panel data, the distribution of T-dimensional vector ($\epsilon_i = (\epsilon_{i1}, \dots, \epsilon_{iT})^{`}$) can be rewritten as:

$$\epsilon_i \sim CSN_{T,T}(0_T, \sigma^2 I_T, -\frac{\lambda}{\sigma} I_T, 0_T, I_T) \quad (5.12)$$

where I is the identity matrix, in which the vector includes the mean of errors, i.e. $\bar{\epsilon}_i = \frac{1}{T}\sum_t \varepsilon_{it}$ and $\tilde{\epsilon}_i^* = (\tilde{\epsilon}_{i1}, \dots, \tilde{\epsilon}_{i,T-1})^{`}$, which indicates the vector of the first T − 1 deviations from the mean ($\tilde{\epsilon}_i^*$). The likelihood function is parameterized in terms of β, $\lambda = \sigma_u/\sigma_v$ and $\sigma^2 = \sigma_u^2 + \sigma_v^2$, where the incidental parameters problem is avoided and inefficiency is allowed to be time-varying. By adopting the point estimator of Battese and Coelli (1988), the composed error can be written as:

$$\epsilon_{it} = y_{it} - \hat{y}_{it} = y_{it} - \hat{\beta}^{`} x_{it} - \hat{\alpha}_i \quad (5.13)$$

In equation (5. 13), the value of $\hat{\alpha}_i$ can be estimated through the method proposed by Chen et al. (2014), where

$$\hat{\alpha}_i^M = \bar{y}_i - \hat{\beta}^{`} \bar{x}_i + \sqrt{\frac{2}{\pi}} \hat{\sigma}_u \quad (5.14)$$

where $\hat{\beta}^{`}$ and $\hat{\sigma}_u$ are the within maximum likelihood estimation (WMLE) estimates. Then, based on Battese and Coelli (1988), the efficiency term can be calculated as:

$$\text{EFF}_{it} = E(\exp(-u_{it})|\epsilon_{it}) \tag{5.15}$$

5.3.3.2 Dynamic Doubly Censored Tobit Model

In the second step, we employ the limited dependent variable model to investigate the effects of diversification on bank efficiency, since each set of the efficiency scores is limited to values between 0 and 1. Furthermore, in the model used here, the distribution of the dependent variable is expected to be half normal rather than normal, and the error terms cannot meet the assumption of a normal distribution. Thus, non-censored estimates such as OLS will be biased and inappropriate for estimation, since in OLS, the dependent variable can take on a negative or positive real value. The consequences of ignoring fractionality may result in biased estimation and inconsistent parameter estimates (Greene, 1980). Therefore, we set up the dynamic doubly censored Tobit model with a left censored bound of zero and a right censored bound of one to regress bank-level efficiency scores against banks' income diversification and several control variables.

The dynamic Tobit estimation was developed by Elsas and Florysiak (2015), based on Loudermilk (2007). With this estimator, the distribution of the unobserved fixed effects is assumed to be conditional on the initial value of the dependent variable and the time averages of the exogenous explanatory variables (Wooldridge, 2005). In essence, this modelling strategy allows for firm heterogeneity. An additional important feature of this approach is that, unlike the dynamic Tobit model of Loudermilk (2007), the approach by Elsas and Florysiak (2015) does not require balanced panel data and is robust to missing data in unbalanced panels.

The Elsas and Florysiak (2015) dynamic Tobit model is suitable for unbalanced dynamic panel data with a fractional dependent variable (DPF estimator) and can capture fixed effects in estimating the unobserved, time-invariant firm heterogeneity. In this approach, the DPF estimator is a doubly censored Tobit estimator employing a latent variable specification to estimate the fractional nature of the dependent variable. The specification includes corner observations at 0 and 1, with a lagged dependent variable. In its general form, we have:

$$y_{it}^{*} = z_{it}\gamma + g(y_{i,t-1})\rho + c_i + u_{it}, \tag{5.16}$$

$$u_{it}|(z_{it}, y_{i,t-1}, \dots, y_{i0}, c_i) \sim N(0, \sigma_u^2). \tag{5.17}$$

The observable doubly censored dependent variable with two possible corner outcomes is as follows:

$$y_{it} = \begin{cases} 0 & if \;\; y_{it}^* \leq 0 \\ y_{it}^* & if \;\; 0 < y_{it}^* < 1 \\ 1 & if \;\; y_{it}^* \geq 1 \end{cases} \tag{5.18}$$

where z_{it} refers to strictly exogenous regressors, c_i indicates the unobserved effect, and u_{it} is a normally distributed error term; y_{it}^* is the unobserved latent variable, which is set equal to zero when it is below zero and to one when it is greater than one. The joint density of $(y_{i1}, \dots, y_{iT})$ given (y_{i0}, z_i, c_i) is given by:

$$f(y_{i1}, \dots, y_{iT} | y_{i0}, z_i, c_i) = \sum_{t=1}^{T} f_t \, (y_{it} | w_{it}, c_i; \theta) \tag{5.19}$$

As the density of $y_{it} = (y_{i1}, \dots, y_{iT})$ given (y_{i0}, z_i, c_i), to proceed with the estimation it is necessary to specify the density of c_i given (y_{i0}, z_i, c_i). Elsas and Florysiak's DPF estimator specifies a conditional distribution for unobserved heterogeneity c_i based on Loudermilk (2007). The unobserved fixed-effects distribution is assumed to be:

$$c_i = \alpha_0 + \alpha_1 y_{i0} + \bar{\grave{z}}_{it} \alpha_2 + \varepsilon_i \tag{5.20}$$

where the error term ε_i is normally distributed, and $\bar{\grave{z}}_{i,t}$ is the time-series average of z_{it}. Unlike the Tobit estimation developed by Loudermilk (2007), rather than including the term z_{it}, the DPF estimator assumes that the fixed effects distribution depends on time-series averages of the exogenous variables; hence, it does not require the fixed effects to depend on a balanced panel. The substitution for c_i is produced by:

$$P\left(y_{it} = 0 \middle| w_{it}, \bar{z}_{it}^{`}, y_{i0}, \alpha_i\right)$$

$$= \Phi\left(\frac{-\bar{z}_{it}^{`}\gamma - g_{i,t-1}\rho - \alpha_0 - \alpha_1 y_{i0} - \alpha_2 \bar{z}_i^{`} - \alpha_i}{\sigma_u}\right) \tag{5.21}$$

$$P\left(y_{it} = 1 \middle| w_{it}, \bar{z}_{it}^{`}, y_{i0}, \alpha_i\right)$$

$$= \Phi\left(\frac{\bar{z}_{it}^{`}\gamma + g_{i,t-1}\rho + \alpha_0 + \alpha_1 y_{i0} + \alpha_2 \bar{z}_i^{`} + \alpha_i - 1}{\sigma_u}\right) \tag{5.22}$$

and

$$\frac{\partial P(y_{it} \leq y | w_{it}, \bar{z}_{it}^{`}, y_{i0}, \alpha_i)}{\partial y}$$

$$= \frac{1}{\sigma_u}\phi\left(\frac{y_{it} - \bar{z}_{it}^{`}\gamma - g_{i,t-1}\rho - \alpha_0 - \alpha_1 y_{i0} - \alpha_2 \bar{z}_i^{`} - \alpha_i}{\sigma_u}\right) \tag{5.23}$$

Therefore, the log-likelihood function can be estimated by integrating the density of $(y_{i1}, \dots, y_{iT})$ given (y_{i0}, z_i, c_i) against the distribution of α_i:

$$L = \sum_{i=1}^{n} log\left\{\int \left[\prod_{t=1}^{T} f_t\left(y_{it} \middle| w_{it}, \bar{z}_{it}^{`}, y_{i0}, \alpha_i; \theta\right)\ \right] \frac{1}{\sigma_a}\phi\left(\frac{a}{\sigma_a}\right) da\right\} \tag{5.24}$$

After iterated expectations, defining

$\widehat{\Phi}_1 = \Phi((-w_{it}\beta - \alpha_0 - \alpha_1 y_{i0} - \alpha_2 \bar{z}_i^{`})/\sigma_u)$ , $\widehat{\Phi}_2 = \Phi((1 - w_{it}\beta - \alpha_0 - \alpha_1 y_{i0} - \alpha_2 \bar{z}_i^{`})/\sigma_u)$, $\hat{\phi}_1 = \phi((-w_{it}\beta - \alpha_0 - \alpha_1 y_{i0} - \alpha_2 \bar{z}_i^{`})/\sigma_u)$, $\hat{\phi}_2 = \phi((1 - w_{it}\beta - \alpha_0 - \alpha_1 y_{i0} - \alpha_2 \bar{z}_i^{`})/\sigma_u)$ and $\sigma_v = \sigma_u + \sigma_a$. (5.25)

The conditional mean function can be described as:

$$r(w_{it}, \bar{z}_{it}^{`}, y_{i0}; \theta)$$

$$= \Phi\left(\frac{w_{it}\beta + \alpha_0 + \alpha_1 y_{i0} + \alpha_2 \bar{z}_i^{`} - 1}{\sigma_v}\right) + \left(w_{it}\beta + \alpha_0 + \alpha_1 y_{i0} + \alpha_2 \bar{z}_i^{`}\right)\left[\widehat{\Phi}_2 - \widehat{\Phi}_1\right]$$

$$+\sigma_v[\widehat{\Phi}_1 - \widehat{\Phi}_2], \qquad (5.26)$$

and estimation of average partial effects is given by:

$$\frac{\partial r(w_{it}, \bar{z}_i^{`}, y_{i0}; \theta)}{\partial w_j}\Big|_{\theta=\hat{\theta}}$$

$$= \frac{1}{N}\sum_{i=1}^{N} \beta_j \left\{1 + \left[\frac{1-\sigma_v}{\sigma_v}\right]\hat{\phi}_2 - [\frac{1-\sigma_v}{\sigma_v}](w_{it}\beta + \alpha_0 + \alpha_1 y_{i0} + \alpha_2 \bar{z}_i^{`})(\hat{\phi}_2 - \hat{\phi}_1)\right\} \qquad (5.27)$$

As the distribution of c_i is specified in terms of observables and a normally distributed error term, partial effects on $P(y_{it} = 0|w_{it}, c_i)$ and $P(y_{it} = 1|w_{it}, c_i)$ can then be computed.

5.4 Empirical Estimation

5.4.1 Estimating Efficiency Scores for Chinese Banks

5.4.1.1 Specification for the Empirical Model of Stochastic Frontier Analysis

We first establish the specification for SFA, and considering the relatively short panel length of the data for Chinese banks, we apply the analysis with the method of within maximum likelihood estimation (WMLE). In the estimation, the cost and profit frontier models are expressed in Eqs 5.28 and 5.29 (our empirical cost and profit frontier models are shown in Eqs 5.30 and 5.31):

$$TC_{it} = f(Y_{it}, W_{it}, Z_{it}; \beta) + \nu_{it} + u_{it} \quad \mathrm{i} = 1, \dots \mathrm{I}, \quad \mathrm{t} = 1, \dots \mathrm{T} \tag{5.28}$$

$$TP_{it} = f(Y_{it}, W_{it}, Z_{it}; \beta) + \nu_{it} - u_{it} \quad \mathrm{i} = 1, \dots \mathrm{I}, \quad \mathrm{t} = 1, \dots \mathrm{T} \tag{5.29}$$

where following Lensink and Meesters (2014), the functional form of $f(Y_{it}, W_{it}, Z_{it}; \beta)$ is estimated by translog form. TC_{it} and TP_{it} refer to the observed total cost and profits before tax for bank i at time t; Y_{it} and W_{it} represent the vectors of output and input prices for a specific bank; Z_{it} refers to a vector of control variables, and β is a vector of technology parameters. In SFA, the error term can be disentangled into two elements: v_{it} is the measurement error and random effects, which are assumed to follow a normal distribution, i.e. v_{it}~iid $N(0\,, \sigma_v^2)$; and u_{it} is the inefficiency term, which is assumed to follow a half-normal distribution, i.e. $u_{it} \sim N^+(0, \sigma_v^2)$. w_{it} is the effect of unobserved factors, which follows a truncated normal distribution with zero mean and constant variance. Because it is necessary to ensure that all dependent variables are positive, we follow Dong et al. (2016) and delete all observations of the profit variable with a negative sign.

SFA uses a parametric approach, which requires specification of the functional form of the production function and the distribution of its error terms. According to the duality theorem, the cost function must be linearly homogeneous in input prices, whereas continuity requires that the second-order parameters must be symmetric. Hence, we scale the total costs and input price by one price, w_{jit}, to impose a linear homogeneity restriction on the model (Dong et al., 2016). In addition, there are standard symmetry restrictions, where $\gamma_{jk} = \gamma_{kj}$ and $\beta_{nm} = \beta_{mn}$. Thus we specify the cost function as:

$$\ln\left(\frac{TC_{it}}{w_{kit}}\right) = \alpha_i + \sum_{m=1}^{3} \beta_m lny_{mit} + \frac{1}{2}\sum_{m=1}^{3}\sum_{n=1}^{3} \beta_{mn} lny_{mit} lny_{nit} + \gamma_1 ln(w_{jit}/ w_{kit}) + \frac{1}{2}\gamma_2 ln(w_{jit}/w_{kit})^2 + \frac{1}{2}\sum_{m=1}^{3} \psi_{mj} lny_{mit}(w_{jit}/w_{kit}) + \phi_1 ln\mathrm{Z}_{it} + \frac{1}{2}\phi_2 ln\mathrm{Z}^2{}_{it} + \sum_{m=1}^{3} lny_{mit} ln\mathrm{Z}_{it} + \xi ln(w_{jit}/w_{kit}) ln\mathrm{Z}_{it} + \theta_1 T + \frac{1}{2}\phi_2 T^2 + \sum_{m=1}^{3} k_m lny_{mit} T + \rho ln(w_{jit}/w_{kit})T + \eta ln\mathrm{Z}_{it} T + \nu_{it} + u_{it} \tag{5.30}$$

As we utilise fixed-effect estimation, in this equation, α_i is the unobserved "heterogeneity" of utility i, which is treated as fixed; the dependent variable of the cost function $\ln(TC_{it})$ refers to logarithm of total cost, including labour, interest, and other costs; lny_{mit} indicates the logarithm of the output of a specific bank; lnw_{jit} indicates the logarithm of input price of a specific bank; lnE_{it} refers to the environmental variable, which is the logarithm of total equity of a specific bank; and u_{it} is the inefficiency term, with an explicit function of environmental variables that impact each bank's best performance.

With regards to profit efficiency, we utilise an alternative measure, which is calculated using a translog functional model similar to that used for the cost efficiency. Instead of total cost, we use the logarithm of profit before tax $\ln(TP_{it})$, along with the same independent variables as used in the cost function. Hence, we specify the profit function as:

$$\ln(TP_{it}) = \alpha_i + \sum_{m=1}^{3} \beta_m lny_{mit} + \frac{1}{2}\sum_{m=1}^{3}\sum_{n=1}^{3} \beta_{mn} lny_{mit} lny_{nit} + \sum_{j=1}^{2} \gamma_j\, lnw_{jit} + \frac{1}{2}\sum_{j=1}^{2}\sum_{k=1}^{2} \gamma_{jk} lnw_{jit} lnw_{kit} + \frac{1}{2}\sum_{m=1}^{3}\sum_{j=1}^{2} \psi_{mj} lny_{mit} lnw_{jit} + \phi_1 ln\mathrm{Z}_{it} + \frac{1}{2}\phi_2 ln\mathrm{Z}^2{}_{it} + \sum_{m=1}^{3} lny_{mit} ln\mathrm{Z}_{it} + \sum_{j=1}^{2} \xi_J lnw_{jit} ln\mathrm{Z}_{it} + \theta_1 T + \frac{1}{2}\phi_2 T^2 + \sum_{m=1}^{3} k_m lny_{mit} T + \sum_{j=1}^{2} \rho_J lnw_{jit} T + \eta ln\mathrm{Z}_{it} T + \nu_{it} - \ u_{it} \tag{5.31}$$

5.4.1.2 Empirical Results of SFA

Table 5.1 presents the estimation results of the cost and profit frontier models using maximum likelihood techniques. As my main interest here is to estimate the diversification effects, we do not discuss the estimated coefficients on other variables of the frontiers in detail. However, stochastic frontier analysis fulfils the theoretical requirements for a valid cost function. More specifically, the tests in terms of the monotonicity of the cost function are satisfied, as the estimates for $\partial \ln(\mathrm{TC}) \,/\, \partial\ln(Q_i)$ and $\partial \ln(\mathrm{TC}) \,/\, \partial\ln(W_i)$ are all positive, thus indicating that the cost function is non-decreasing in outputs and input prices.

Table 5.1 Parameter estimates of the cost and profit frontiers

Cost frontier			Profit frontier		
Variables	Coefficient	Standard error	Variables	Coefficient	Standard error
lny1	0.486**	0.201	lny1	0.178	0.203
lny2	0.390*	0.230	lny2	-0.435*	0.231
lny3	0.449**	0.212	lny3	0.899***	0.185
0.5*(lny1)^2	0.157***	0.021	0.5*(lny1)^2	0.192***	0.020
lny1*lny2	-0.333***	0.018	lny1*lny2	-0.271***	0.009
lny1*lny3	0.114**	0.048	lny1*lny3	0.021*	0.011
0.5*(lny2)^2	0.24***	0.023	0.5*(lny2)^2	0.385***	0.017
lny2*lny3	-0.005	0.023	lny2*lny3	-0.075***	0.011
0.5*(lny3)^2	-0.041	0.032	0.5*(lny3)^2	-0.004	0.016
ln(w1/w2)	1.083***	0.155	lnw1	1.392***	0.398
			lnw2	-0.599***	0.172
0.5*(ln(w1/w2))^2	0.039**	0.017	0.5*(lnw1)^2	0.068	0.058
			lnw1*lnw2	-0.076**	0.031
			0.5*(lnw2)^2	0.051***	0.019
lny1*ln(w1/w2)	-0.070***	0.021	lny1*lnw1	-0.142***	0.044
			lny1*lnw2	0.069**	0.027
lny2*ln(w1/w2)	-0.004	0.022	lny2*lnw1	-0.114**	0.051
			lny2*lnw2	-0.009	0.023
lny3*ln(w1/w2)	0.037*	0.019	lny3*lnw1	0.091**	0.037
			lny3*lnw2	0.021	0.018
lnz	-0.896***	0.168	lnz	-0.176	0.316
0.5*(lnz)^2	-0.037	0.023	0.5*(lnz)^2	-0.032	0.032
lnz*lny1	0.072***	0.026	lnz*lny1	0.064***	0.020
lnz*lny2	0.106***	0.025	lnz*lny2	-0.030**	0.012
lnz*lny3	-0.096***	0.014	lnz*lny3	0.038***	0.010
lnz*ln(w1/w2)	0.039*	0.023	lnz*lnw1	0.159***	0.060
			lnz*lnw2	-0.072**	0.031
T	0.283***	0.036	T	0.219***	0.070
0.5*(T^2)	0.001	0.002	0.5*(T^2)	0.003	0.003
T*ln(w1/w2)	0.005	0.004	T*lnw1	0.006	0.008
			T*lnw2	0.008*	0.004
T*lny1	-0.024***	0.004	T*lny1	-0.020	0.015
T*lny2	-0.021***	0.006	T*lny2	0.001	0.011
T*lny3	0.005	0.005	T*lny3	-0.005	0.005
T*lnz	0.029***	0.007	T*lnz	0.016	0.021
Constant	2.536***	0.658	Constant	1.788***	0.598

The yearly mean efficiency estimations from 2005 to 2016 for the full sample and three sub-groups, namely, G-SIBs, D-SIBs and N-SIBs, are plotted in Figures 5.1 and 5.2.

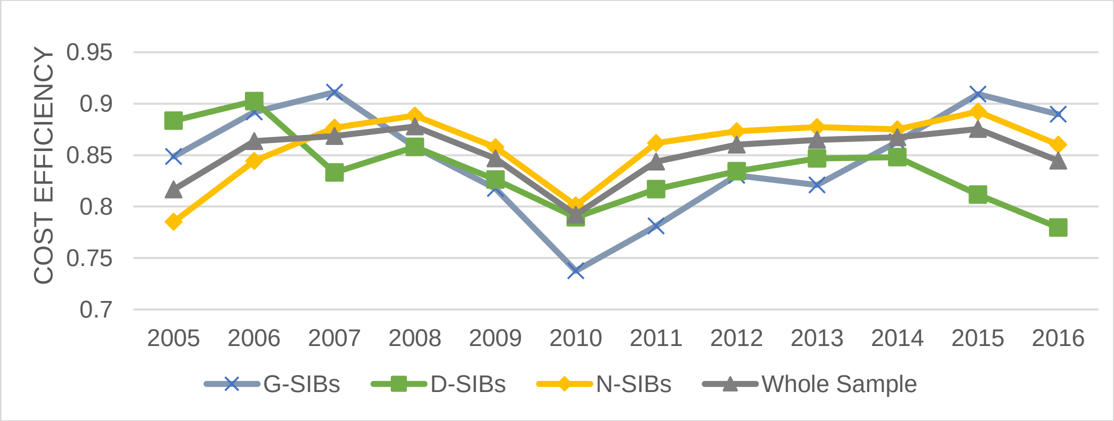


Figure 5.1 Yearly mean cost efficiency for the whole sample and three sub-groups

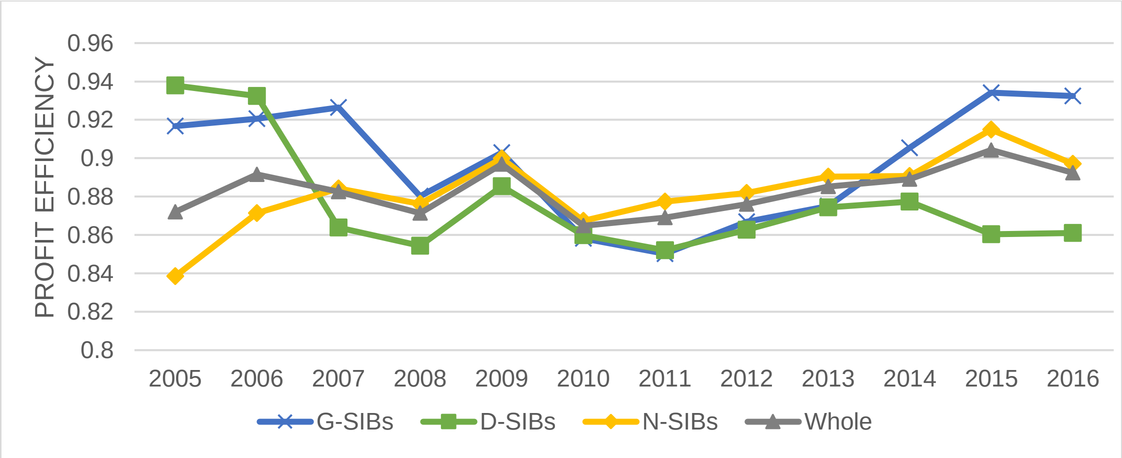


Figure 5.2 Yearly mean profit efficiency for the whole sample and three sub-groups

It can be observed that the average of both cost and profit efficiency scores exhibit an increasing tendency from 2005 to 2008 and then begin to decline, reaching the lowest point in 2010. Subsequently, the efficiency of Chinese commercial banks improves steadily, to achieve a relatively high point in 2015. The three sub-groups each follow a similar trend to that of the overall banking sector, exhibiting a general increase from 2005 to 2008 and then a decrease, reaching the lowest point in 2010, and then starting to rise once again. In more detail, in 2005, D-SIBs were the most efficient bank group in the Chinese banking market; however, their efficiency decreased dramatically after 2006. G-SIBs generally maintained a cost efficiency score midway between those of the other two groups. It seems that the efficiency of those banks does not benefit greatly from their scale of assets or scope of business.

5.4.2 Determination of Diversification Effects on Cost and Profit Efficiency

We apply an estimator designed to be unbiased in the context of unbalanced dynamic panel data, with a fractional dependent variable to regress the efficiency scores on the diversification level. This is within the family of censored regression models. The particular functional form we adopt is the dynamic Tobit model, as against the Probit model. The dynamic Tobit model is extensively discussed in Hu (2002), Wooldridge (2005) and Li and Zheng (2008). According to Wooldridge (2005), the dynamic Tobit model is described as:

$$y_{it} = max\left[0, \boldsymbol{z}_{it}\boldsymbol{\gamma} + \boldsymbol{g}\left(y_{i,t-1}\right)\boldsymbol{\rho} + c_i + u_{it}\right]$$

$$u_{it}\left|y_{i,t-1}, \ldots\ldots y_{i0}, \boldsymbol{z}_i, c_i\right.\sim Normal(0, \delta_u^2) \tag{5.32}$$

where y_{it} is observed response variable of interest on the ith agent in time period t which depends on the explanatory variables $\boldsymbol{z}_{it}$, the lags of the dependent variable $y_{i,t-1}$and the unobserved individual heterogeneity c_i. u_{it} is the error terms, which are assumed to be i.i.d. normally distributed conditional on $\left(y_{i,t-1} \ldots\ldots y_{i,0}, \{\boldsymbol{z}_{it}\}_{t=2}^{T}, c_i\right)$.

In a dynamic panel Tobit model, researchers often take the following form (Hu, 2002):

$$y_{it}^* = x_{it}\beta + y_{i,t-1}\lambda + \epsilon_{it}$$

$$y_{it} = max\{y_{it}^*, 0\}$$

$$\epsilon_{it} = a_i + u_{it}, \qquad i = 1, \ldots \ldots N; t = 1, \ldots \ldots T \tag{5.33}$$

where y_{it}^* is latent dependent variable, $y_{i,t-1}$ is first lag of the observed dependent variable, x_{it} is a vector of exogenous variables, β are the regression coefficients, λ is the coefficient on the lagged dependent variable. Further, the component a_i is unobserved individual effect and u_{it} is the error terms. In the panel data Tobit model, the variable of $y_{i,t-1}^*\lambda$ introduces the dynamics into the system. For our research interests, we have:

$$EFF_{it} = \lambda EFF_{it-1} + (DIV_{it}, Lerner_{it}, NIM_{it}, ETA_{it}, CIR_{it})'\beta + \alpha_i + u_{it} \qquad (5.34)$$

Empirical results which are estimated by Eq. (5.34) are reported in Table 5.2 and Table 5.3 for whole sample and in Table 5.4, Table 5.5, Table 5.6, Table 5.7, Table 5.8 and Table 5.9 for three Chinese banking groups (G-SIBs, D-SIBs and N-SIBs). In this dynamic panel Tobit model, the dependant variables are EFF_{it} which is represented by two different measurements of banks' efficiency, namely, cost and profit efficiency. In addition to the lagged dependent variables in the model, the vector of exogenous variables contains $DIV_{it}, Lerner_{it}, NIM_{it}, ETA_{it}, CIR_{it}$; where DIV_{it} is the variable of our main interest, which captures the level of diversification, represented respectively by the Herfindahl-Hirschman Index and the shares of three non-interest components over total income;$Lerner_{it}$ is the Lerner index; NIM_{it} is the ratio of net interest revenue to total earning assets; ETA_{it} is the ratio of equity over total assets; and CIR_{it} is the cost-to-income ratio.

5.4.2.1 Income Diversification and Efficiency: Whole Sample

Having estimated the efficiency scores, we next apply the dynamic Tobit model with the DPF estimator to investigate their determinants. In addition to the above input price and output variables, a number of variables are included to explain the efficiency scores. Table 5.2 presents the results for the Chinese banking industry as a whole.

Table 5.2 Income diversification and banks' efficiency for the whole sample, 2005 to 2016

This table reports the results of the dynamic Tobit estimation. Our dependent variables are cost efficiency and profit efficiency, which are estimated via stochastic frontier analysis. .I(t-1) refers to the dependent variables lagged by one period. HHI indicates income diversification using the Herfindahl-Hirschman index with the components of interest income and three component activities under non-interest income. Lerner indicates the Lerner index calculated by (bank price - marginal cost)/bank price, NIM indicates net interest revenue over total earning assets, ETA refers to equity / total assets, and CIR indicates the cost-income ratio. Figures in brackets are standard errors. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	Cost efficiency	Profit efficiency
I_(t-1)	0.518***	0.828***
	(0.051)	(0.03)
HHI	-0.143**	-0.072**
	(0.059)	(0.031)
Lerner	-0.276***	-0.001
	(0.048)	(0.033)
NIM	2.135***	0.003
	(0.698)	(0.451)
ETA	0.662***	0.593***
	(0.231)	(0.163)
CIR	-0.041	0.044
	(0.051)	(0.032)
Constant	0.460***	0.121***
	(0.064)	(0.036)
Log likelihood	579.193	614.549
LR test (p-value)	0.000	0.000
Observations	413	413

As can be seen from the table, both the cost and profit efficiency exhibit a consistent sign, with negative coefficients at the 1% significance level. This outcome is consistent with Cheng (2015), who finds that income diversification could decrease both cost and profit efficiency in the Chinese banking sector. A plausible explanation for this effect is that the overall level of operational ability in the Chinese banking sector is low and the internal capital market is inefficient. As a result, internal reallocation of resources may have led to over-investment or under-investment, which would increase the costs of coordination and management, leading to inefficiency.

One of the control variables employed is the Lerner index, which measures a bank's level of market power. In the estimation results, both the cost and profit efficiency scores have a negative correlation with the Lerner index, indicating that the higher the market power of the bank is, the less efficient the bank will become. This result is consistent with the notion that banks tend to pursue a 'quiet life'; that is, banks with higher monopoly power seem to allow costs to rise as a consequence of slack management. When market power prevails, managers may pursue objectives other than profit maximization, and they do not have incentives to work hard to keep costs under control, a situation that leads to a reduction in cost efficiency (Koetter et al., 2008; Delis and Tsionas, 2009; Ariss, 2010).

It is conceivable that components of the non-interest business may perform differently than the overall non-interest activities. To find further evidence for diversification effects across different components of non-interest income, we divide the non-interest income into three categories, namely, fee and commissions, trading, and other income; the results are reported in Table 5.3.

Table 5.3 Results for three components of non-interest income and bank efficiency for Chinese banks, 2005 to 2016

This table reports the results of the dynamic Tobit estimation. Our dependent variables are cost efficiency and profit efficiency, which are estimated via stochastic frontier analysis. It-1 refers to the dependent variables lagged by one period. COM is the ratio of net fee and commission incomes to total operating income; TRA is the ratio of net trading income to total operating income; OTH is the ratio of net other operating income to total operating income. Lerner is the Lerner index calculated as (bank price - marginal cost)/bank price, NIM is the net interest revenue over total earning assets, ETA refers to equity over total assets, and CIR indicates the cost-income ratio. Figures in brackets are standard errors. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	Cost efficiency	Profit efficiency	Cost efficiency	Profit efficiency	Cost efficiency	Profit efficiency
I_(t-1)	0.484***	0.822***	0.522***	0.823***	0.516	0.827***
	(0.043)	(0.031)	(0.059)	(0.029)	(0.404)	(0.028)
COM	-0.454***	-0.152***				
	(0.083)	(0.054)				
TRAD			0.471**	0.136		
			(0.185)	(0.114)		
Other					-2.234**	-0.091
					(1.078)	(0.196)
Lerner	-0.288***	-0.003	-0.302***	-0.024	-0.327	-0.02
	(0.046)	(0.032)	(0.047)	(0.03)	(0.435)	(0.03)
NIM	1.982***	0.075	3.323***	0.539	2.352	0.423
	(0.621)	(0.436)	(0.672)	(0.408)	(3.105)	(0.417)
ETA	0.781***	0.594***	0.551**	0.308**	0.307	0.358
	(0.216)	(0.161)	(0.229)	(0.145)	(1.184)	(0.142)
CIR	-0.076	0.04	-0.011	0.037	-0.055	0.039
	(0.049)	(0.032)	(0.049)	(0.03)	(0.344)	(0.03)
Constant	0.506***	0.125***	0.401***	0.123***	0.397	0.120***
	(0.056)	(0.036)	(0.063)	(0.033)	(0.688)	(0.033)
Log likelihood	586.916	615.78	564.058	706.621	405.880	719.503
LR test (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
Observations	413	413	404	404	411	411

As can be seen from Table 5.3, all lagged dependent variables exert a significant and positive effect on the current efficiency level. In particular, the results indicate that Chinese banks could reap efficiency advantages from a shift towards trading activities. However, both the fee-based and other activities could bring an efficiency discount in the process of income diversification.

5.4.2.2 Income Diversification and Efficiency across Banking Groups

Several studies claim that the strength of the relationship between income diversification and banks' efficiency could be greatly affected by bank business scale. Specifically, large banks should have a higher share of non-interest income and a better cost management capacity, whereas at the same time, given the agency problem, managing organized chaos would lead to a reduction in operational efficiency. To investigate whether the diversification effect on banks' efficiency varies with bank size, we test the effects across the three groups: G-SIBs, D-SIBs and N-SIBs. [5]

China's Global Systemically Important Banks

[5] As the small sample size might result in an incidental parameters problem, this thesis also applies a robustness test by using dummy variables to catalogue the three sub-groups. The robustness test results are reported in the Appendix.

Table 5.4 reports the results of estimating the dynamic Tobit model with the DPF estimator with particular reference to G-SIBs.

Table 5.4 Income diversification and banks' efficiency for Chinese G-SIBs, 2005 to 2016

This table reports the results of the dynamic Tobit estimation. Our dependent variables are cost efficiency and profit efficiency, which are estimated via stochastic frontier analysis. It-1 refers to the dependent variables lagged by one period. HHI indicates income diversification using the Herfindahl-Hirschman index with the components of interest income and three component activities under non-interest income. Lerner indicates the Lerner index calculated as (bank price - marginal cost)/bank price, NIM indicates net interest revenue over total earning assets, ETA refers to equity over total assets, and CIR indicates the cost-income ratio. Figures in brackets are standard errors. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	Cost efficiency	Profit efficiency
I_(t-1)	0.984***	0.797***
	(0.035)	(0.04)
HHI	-0.613***	-0.236***
	(0.055)	(0.051)
Lerner	-0.642***	-0.453***
	(0.069)	(0.07)
NIM	1.227	-1.730***
	(0.802)	(0.675)
ETA	4.200***	2.213***
	(0.391)	(0.336)
CIR	-0.001	-0.401***
	(0.069)	(0.067)
Constant	0.142**	0.490***
	(0.061)	(0.067)
Log likelihood	365.275	236.676
LR test (p-value)	0.000	0.000
Observations	42	42

The findings show that banks' income diversification has significant and negative effects on both cost and profit efficiency of G-SIBs, thus providing evidence that diversified banks incur an efficiency discount compared with banks that focus on traditional sources of interest income. The coefficient on cost efficiency is -0.613, whereas that on profit efficiency is -0.236, both significant at the 1% level. This result indicates that higher income diversification would lead to greater discounts to cost efficiency than to profit efficiency.

In addition, the Lerner index also exhibits a negative effect on banks' efficiency level, which is consistent with the results for the whole sample. Meanwhile, for this sub-group, ETA maintains a significant positive coefficient correlated with the banks' efficiency; thus, the capital adequacy in G-SIBs is helpful to improve their efficiency.

China's Domestic Systemically Important Banks

We now move to examine the efficiency effect of diversification for China's domestic systemically important banks (D-SIBs). Table 5.5 reports the results.

Next, we examine the regression results for other variables. First, a significantly negative Lerner index indicates that a higher level of monopoly power for a specific bank could be related to lower efficiency. For D-SIBs, we obtain a greater coefficient on the Lerner index, indicating that for smaller-sized banks, the negative influence from a higher monopoly power would be smoothed compared with the situation for G-SIBs, such that they experience lower discounts with increased monopoly power. Secondly, the equity-to-assets ratio, which measures the financial leverage, exerts a positive effect on banks' efficiency.

Table 5.5 Income diversification and banks' efficiency for Chinese D-SIBs from 2005 to 2015

This table reports the results of the dynamic Tobit estimation. Our dependent variables are cost efficiency and profit efficiency, which are estimated via stochastic frontier analysis. It-1 refers to the dependent variables lagged by one period. HHI indicates income diversification using the Herfindahl-Hirschman index with the components of interest income and three component activities under non-interest income. Lerner indicates the Lerner index calculated as (bank price - marginal cost)/bank price, NIM indicates net interest revenue over total earning assets, ETA refers to equity over total assets, and CIR indicates the cost-income ratio. Figures in brackets are standard errors. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	Cost efficiency	Profit efficiency
I_(t-1)	0.842***	1.003***
	(0.025)	(0.016)
HHI	-0.162***	-0.105***
	(0.056)	(0.045)
Lerner	-0.278***	-0.086***
	(0.037)	(0.029)
NIM	1.705**	-2.938***
	(0.837)	(0.663)
ETA	0.899***	1.179***
	(0.3)	(0.247)
CIR	-0.045	-0.01
	(0.06)	(0.05)
Constant	0.199***	0.074**
	(0.046)	(0.033)
Log likelihood	380.025	211.442
LR test (p-value)	0.000	0.000
Observations	97	97

Other Chinese Banks

Table 5.6 reports the results for other Chinese banks.

Table 5.6 Income diversification and banks' efficiency for Chinese N-SIBs, 2005 to 2016

This table reports the results of the dynamic Tobit estimation. Our dependent variables are cost efficiency and profit efficiency, which are estimated via stochastic frontier analysis. It-1 refers to the dependent variables lagged by one period. HHI indicates income diversification using the Herfindahl-Hirschman index with the components of interest income and three component activities under non-interest income. Lerner indicates the Lerner index calculated as (bank price - marginal cost)/bank price, NIM indicates net interest revenue over total earning assets, ETA refers to equity over total assets, and CIR indicates the cost-income ratio. Figures in brackets are standard errors. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	Cost efficiency	Profit efficiency
I_(t-1)	0.523***	0.454*
	(0.100)	(0.241)
HHI	0.019	0.009
	(0.102)	(0.157)
Lerner	-0.299***	-0.045
	(0.104)	(0.16)
NIM	4.507***	5.657**
	(1.337)	(2.633)
ETA	0.123	0.01
	(0.459)	(0.835)
CIR	-0.044	0.042
	(0.096)	(0.126)
Constant	0.437***	0.394
	(0.115)	(0.251)
Log likelihood	49.290	1365.163
LR test (p-value)	0.000	0.000
Observations	274	274

As can be seen from the table, these results differ from those for the other two sub-groups. Here, the findings indicate a significant relationship between the diversification index (HHI) and efficiency scores of Chinese N-SIBs. This suggests that small banks may possess operational advantages that yield higher efficiency, with risk management and project management ensuring efficiency when there is an increase in high-technology requirements and highly leveraged non-interest products (Girardone et al., 2004; Kumbhakar and Wang, 2007).

As reported in Tables 5.4, 5.5 and 5.6, the results reveal a diversification discount to banks' efficiency, which eventually becomes a benefit, across the three categories of G-SIBs, D-SIBs and N-SIBs. It is plausible that the differences in results across the three groups are due to bank size, from large G-SIBs to medium-sized D-SIBs and smaller N-SIBs.

5.4.2.3 Effects of Diversification on Efficiency with Components of Non-interest Activities

We also examine the effects of different types of non-interest activities on the efficiency of Chinese banks. The results for G-SIBs are reported in Table 5.7. For trading income, we find positive coefficients, where an increase in scale of trading income would improve banks' efficiency level. However, commissions and other activities present negative coefficients for both cost and profit efficiency scores at the 1% significance level, indicating that a higher reliance on fee-based and other income is associated with a decrease in banks' efficiency.

Table 5.7 Results for three components of non-interest income and bank efficiency for G-SIBs from 2005 to 2016

This table reports the results of the dynamic Tobit estimation. Our dependent variables are cost and profit efficiency, which are estimated via stochastic frontier analysis. It-1 refers to the dependent variables lagged by one period. COM is the ratio of net fee and commission income to total operating income; TRA is the ratio of net trading income to total operating income; OTH is the ratio of net other operating income to total operating income. Lerner indicates the Lerner index calculated as (bank price - marginal cost)/bank price, NIM indicates net interest revenue over total earning assets, ETA refers to equity over total assets, and CIR indicates the cost-income ratio. Figures in brackets are standard errors. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	Cost efficiency	Profit efficiency	Cost efficiency	Profit efficiency	Cost efficiency	Profit efficiency
I_(t-1)	0.811***	0.643***	1.099***	1.051***	0.927***	0.758***
	(0.021)	(0.032)	(0.068)	(0.052)	(0.029)	(0.03)
COM	-1.321***	-1.085***				
	(0.072)	(0.113)				
TRAD			1.663**	1.341***		
			(0.738)	(0.52)		
Other					-1.193***	-1.415***
					(0.306)	(0.19)
Lerner	-0.701***	-0.274***	-1.155***	-1.125***	-0.736***	-0.302***
	(0.046)	(0.043)	(0.138)	(0.031)	(0.07)	(0.042)
NIM	0.391	-4.141***	7.303***	0.844	1.794**	-3.794***
	(0.498)	(0.585)	(1.38)	(0.573)	(0.838)	(0.55)
ETA	1.825***	1.901***	0.938	0.111	3.511***	3.044***
	(0.165)	(0.198)	(0.683)	(0.248)	(0.432)	(0.282)
CIR	-0.757***	-0.649***	-0.289*	0.328***	0.009	-0.072
	(0.05)	(0.057)	(0.169)	(0.056)	(0.085)	(0.05)
Constant	0.753***	0.795***	0.249*	0.263***	0.12*	0.306***
	(0.047)	(0.061)	(0.149)	(0.07)	(0.066)	(0.044)
Log likelihood	859.121	478.811	200.631	164.166	462.949	620.381
LR test	0.000	0.000	0.002	0.000	0.002	0.000
Observation	42	42	41	41	42	42

Table 5.8 presents the results for D-SIBs. As can be seen from the table, non-interest business components exert different effects on banks' efficiency scores.

Table 5.8 Results for three components of non-interest income and bank efficiency for Chinese D-SIBs from 2005 to 2016

This table reports the results of the dynamic Tobit estimation. Our dependent variables are cost and profit efficiency, which are estimated via stochastic frontier analysis. It-1 refers to the dependent variables lagged by one period. COM is the ratio of net fee and commission income to total operating income; TRA is the ratio of net trading income to total operating income; OTH is the ratio of net other operating income to total operating income. Lerner indicates the Lerner index calculated as (bank price - marginal cost)/bank price, NIM indicates net interest revenue over total earning assets, ETA refers to equity over total assets, and CIR indicates the cost-income ratio. Figures in brackets are standard errors. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	Cost efficiency	Profit efficiency	Cost efficiency	Profit efficiency	Cost efficiency	Profit efficiency
I_(t-1)	0.953***	1.001***	0.959***	1.005***	0.964***	1.023***
	(0.015)	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)
COM	-0.293***	-0.158**				
	(0.084)	(0.072)				
TRAD			2.038***	1.272***		
			(0.464)	(0.381)		
Other					-0.143	-1.215***
					(0.413)	(0.338)
Lerner	-0.239***	-0.094***	-0.348***	-0.16***	-0.269***	-0.109***
	(0.034)	(0.028)	(0.038)	(0.031)	(0.033)	(0.027)
NIM	2.171***	-2.861***	3.046***	-2.355***	2.703***	-2.893***
	(0.769)	(0.657)	(0.778)	(0.65)	(0.772)	(0.64)
ETA	0.846***	1.104***	0.176	0.691***	0.395*	1.039***
	(0.252)	(0.231)	(0.221)	(0.19)	(0.229)	(0.195)
CIR	-0.003	-0.012	0.041	0.010	0.040	0.048
	(0.057)	(0.05)	(0.056)	(0.048)	(0.059)	(0.05)
Constant	0.046	0.076**	0.041	0.076**	0.02	0.042
	(0.039)	(0.033)	(0.039)	(0.033)	(0.039)	(0.033)
Log likelihood	662.498	494.027	650.344	490.229	656.521	498.018
LR test	0.000	0.000	0.000	0.000	0.000	0.000
Observatio ns	97	97	95	95	97	97

Specifically, fee and commissions and other activities have a negative effect on both cost and profit efficiency. The results for all three sub-activities exhibit a similar sign and direction as those for G-SIBs.

Table 5.9 Results for three components of non-interest income and bank efficiency for Chinese NSIBs from 2005 to 2016

This table reports the results of the dynamic Tobit estimation. Our dependent variables are cost and profit efficiency, which are estimated via stochastic frontier analysis. It-1 refers to the dependent variables lagged by one period. COM is the ratio of net fee and commission income to total operating income; TRA is the ratio of net trading income to total operating income; OTH is the ratio of net other operating income to total operating income. Lerner indicates the Lerner index calculated as (bank price - marginal cost)/bank price, NIM indicates net interest revenue over total earning assets, ETA refers to equity over total assets, and CIR indicates the cost-income ratio. Figures in brackets are standard errors. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	Cost efficiency	Profit efficiency	Cost efficiency	Profit efficiency	Cost efficiency	Profit efficiency
I_(t-1)	0.374***	0.380***	0.375***	0.382***	0.376***	0.413***
	(0.053)	(0.057)	(0.049)	(0.058)	(0.051)	(0.064)
COM	-0.321**	-0.214***				
	(0.138)	(0.078)				
TRAD			0.270*	0.052		
			(0.153)	(0.121)		
Other					0.334	0.028
					(0.31)	(0.132)
Lerner	-0.230***	-0.009	-0.232***	-0.008	-0.230***	-0.011
	(0.061)	(0.037)	(0.05)	(0.039)	(0.055)	(0.043)
NIM	2.200***	0.295	2.137***	0.638	2.772***	0.504
	(0.675)	(0.442)	(0.581)	(0.455)	(0.662)	(0.508)
ETA	0.477*	0.300*	0.486**	0.219	0.374*	0.325*
	(0.247)	(0.156)	(0.206)	(0.161)	(0.225)	(0.184)
CIR	-0.043	0.001	-0.062	0.001	-0.045	-0.012
	(0.051)	(0.032)	(0.042)	(0.033)	(0.047)	(0.036)
Constant	0.583***	0.562***	0.574***	0.545***	0.556***	0.524***
	(0.064)	(0.059)	(0.054)	(0.06)	(0.059)	(0.067)
Log likelihood	315.665	486.478	351.333	473.868	386.568	257.604
LR test	0.000	0.000	0.000	0.000	0.000	0.000
Observation	274	274	268	268	272	272

Table 5.9 presents the effects of three components of non-interest activities on bank efficiency for N-SIBs.

By comparing Table 5.9 with Tables 5.7 and 5.8 it can be seen that, among the three components of non-interest income, a larger share of commission and other non-interest activities leads to a decrease in efficiency for smaller banks, whereas they would gain efficiency improvement when further engaging in trading activities. This finding is consistent with the previous results for large-sized G-SIBs and medium-sized D-SIBs.

5.4.3 Discussion of the Results

Evidence regarding the diversification effect on bank efficiency in China indicates that while diversification yields a discount to the efficiency of the overall Chinese banking sector, the negative effects are mainly concentrated among the G-SIBs and D-SIBS. For N-SIBs, which are relatively small banks, no significant evidence for such an adverse effect is found.

The difference in the results among the three groups seems to be associated with bank size and the related issues. As organizations become more complex owing to an increased number of correlated business lines generated from non-interest activities, monitoring becomes more difficult and thus monitoring costs increase (Laeven and Levine, 2009). Moreover, bureaucratic problems are more pronounced in large banks, and this can lead to less-efficient operating outcomes.

The inefficiencies are further related to the additional overhead costs, inefficient cross-subsidization and moral hazard problems (Klein and Saidenberg, 2010). In particular, when large banks - especially systemically important banks – become ever larger, they will be perceived to be TBTF (too big to fail), and regulatory authorities will provide those banks facing serious trouble with rescue packages (Brewer and Jagtiani, 2013). This will create a situation in which managers have incentives to accentuate moral hazard and therefore operate such banks in an inefficient manner. The TBTF problem is prevalent in China, and the Chinese authorities would routinely intervene to support large-sized, and invariably state-owned, banks. As a result, large banks in China would be burdened with the moral hazard problem and, as elsewhere, have incentives to expand high-risk but more-profitable projects, causing increased risk and inefficiency of resource allocation (Hellmann et al., 2000).

Furthermore, larger banks may find it more difficult to avoid information asymmetry and the associated problems. According to De Jonghe et al. (2015), large banks can obtain diversification benefits only if the information environment and institutional setting allow their stakeholders to exercise proper discipline and when there are no incentives to abuse conflicts of interest that lead to inefficiency. In the Chinese context, information asymmetry is strong in large-sized state-owned banks, but less strong in medium-sized joint-stock banks, and weakest in the smaller-sized city banks and rural banks. Therefore, it will be more difficult for the large-sized banks to monitor the expansion of business lines, and easier for smaller banks within the N-SIBs sub-group to monitor the non-interest activities. Hence, smaller banks are able to achieve efficiency with increased levels of diversification.

The structure of banks' business mode also matters. With regard to the relation between the diversification index and efficiency scores, it has been demonstrated that larger banks (G- and D-SIBs) receive a diversification discount when the diversification index increases. Looking deeper into the effects of component non-interest activities, this result could be driven by a large proportion of fee-based and other non-interest income, which negatively affect efficiency, whereas income from trading activity has a positive effect on efficiency.

It is more revealing to consider the diversification effects from a perspective that combines the banking groups and component non-interest activities. According to the statistics in this study, G-SIBs have the highest levels of incomes from both fee and commissions (11.1%) and other income (1.4%), followed by D-SIBs (8.1% and 0.9%, respectively), with N-SIBs having the lowest level of incomes from these components (4.3% and 0.8%, respectively). However, at the same time, N-SIBs hold the highest proportion of trading income in their total non-interest income and a greater balance between trading and fee-based incomes. It follows that the efficiency discount that the larger banks in China receive could be induced by the fact that they are more likely to diversify towards low-efficiency fee-based activities rather than high-efficiency trading activities, whereas smaller banks are able to maintain more efficient and balanced diversification strategies. Consequently, G-SIBs suffer from high levels of inefficiency, and D-SIBs also experience a reduction in efficiency, albeit to a lesser extent, whereas N-SIBs benefit from higher efficiency.

The different effects of diversification on efficiency across bank groups may also be related to the threshold effects of diversification on the level of risk to which banks are exposed. In Chapter 4, we assess the effects of income diversification on risk among Chinese systemically important banks using a threshold model. The results reveal the existence of inverse U-shaped relationships between bank risk and fee-based activity, and between bank risk and trading activity, indicating that there is a threshold point for both of those activities: below the threshold, banks will become less stable, whereas once the banks mature to pass the threshold, they will benefit from increased stability. Compared with fee-based activity, trading activity has a much lower threshold point, where banks can achieve risk reduction with only 0.265% of trading income, rather than 13.899% for fee-based income. In Chapter 4, we also find that the positive effect on banks' overall risk after passing the threshold point is mainly driven by the trading income rather than fee-based income, whereas other activities continue to bring enhanced risk in both the lower and upper regimes.

The fee-based income in the majority of G- and D-SIBs is below the threshold point (with mean values of 10.84% and 7.4%). Then, any increase in fee-based activities by G- and D-SIBs could bring higher risk, in addition to inefficiency. However, the smaller N-SIBs maintain lower levels of both fee-based and other income, whereas the proportion of trading income is greater. For them, this business structure compensates for the diversification discount generated from the high-volatility of fee-based income in the early stages of their development of diversification. From these results, one can expect that the efficiency of Chinese banks would not increase until after the scale of fee-based income for large banks has expanded to pass a certain threshold.

5.5 Conclusion

Using a two-step approach, this chapter examines the efficiency implications of Chinese banks' shift towards a greater share of non-traditional income in their total income. First, efficiency scores of Chinese banks, both cost and profit, are calculated via stochastic frontier analysis using the method of within maximum likelihood estimation (WMLE). The analysis is applied to the whole Chinese banking sector as well as to three sub-groups, i.e. global systemically important banks (G-SIBs), domestic systemically important banks (D-SIBs) and other banks (N-SIBs). The results show that in the sample period from 2005 to 2016, the average of both cost and profit efficiency scores first exhibited an increasing tendency from 2005 to 2008 and then began to decline, reaching the lowest point in 2010. Subsequently, the efficiency of Chinese banks improved steadily, to achieve a relatively high point after the global financial crisis. The three sub-groups each followed a similar trend to that of the overall banking sector.

In the second step, the investigation employs a dynamic Tobit model to examine the unobserved time-invariant bank heterogeneity. We find that for the overall Chinese banking sector, income diversification has an efficiency-destroying effect. However, the effects vary across the banking groups. For Chinese G-SIBs, diversification has a significant harmful effect on both cost and profit efficiency. For D-SIBs, the effects are similar, but the discount is less. For N-SIBs, diversification has a positive effect on their efficiency level. The differences in empirical results could be explained by the additional overhead cost, inefficient cross-subsidization and moral hazard problems.

After decomposing non-interest activities into three components (fee-based, trading and other activities), it is found that the diversification discount is generated from fee-based and other income activities, whereas trading activity can improve banks' efficiency level. The result is shaped by banks' internal business structure, as larger banks have an incentive to expand highly volatile and less-effective fee and other non-interest incomes, but smaller banks are more likely to diversify towards less risky and more effective trading activity.

Chapter 6

Chapter 6 Conclusion

This chapter summarizes the main research findings and the implications of the study, and suggests avenues for future research.

Chapter 6

Conclusion

6.1 Main Findings

Profound changes in the business modes of the global banking industry have transformed the banks' income structure over the past four decades. As a result, while the interest margin remains the principal source of income for banks, non-interest income has increased its importance in banks' total revenue. Amid the global trend of income diversification, Chinese banks lately have also become active in pursing business diversification which has raised significance of non-traditional income in their revenue structure.

Shifting to non-traditional business to earn fee-based income represents a major challenge for banks. Whether the shift is beneficial has sparked off fresh interest in the literature and a lively debate that centres on the merits and pitfalls of such diversification. The current thesis contributes to this debate by investigating income diversification in the Chinese banking industry as a case of study particularly for bank diversification in emerging market economies which have been too often overlooked in the existing literature.

We consider the diversification effects in three aspects, namely the effect on banks' profits, risk exposure and efficiency scores. In the study, the overall Chinese banking sector is classified into three sub-groups, namely global systemically important, domestic systemically important, and non-systemically important banks. The grouping is to reflect the complexity of the Chinese banking industry which is fast rising to become the largest one of the world. By providing a comprehensive yet well-structured study, this thesis offers to improve our understanding of the desirability of and main diversification effects on banks.

In Chapter 2, we introduce the background to the rise and development of income diversification in China. A multitude of factors have acted as the driving forces behind the change. These primarily include regulatory changes, growing completions in the banking environment and unfolding of the financial reforms in China. Consequently, non-traditional and fee-based income has become a substantial part of Chinese banks' total revenue.

The following chapters then move to examine the effects of the income diversification process on Chinese banks. The first of them, i.e. Chapter 3 examines to what extent income diversification would affect the profitability of Chinese banks, which is a first step in analysing the performance of the Chinese banking industry in the age of bank diversification. Employing a dynamic SYS-GMM panel data model to evaluate the performance effects of income diversification, this chapter finds that for the Chinese banking sector as a whole there exists a diversification discount, suggesting that a shift from traditional banking business to mixed business lines negatively affects bank performance.

However, structurally, the results are rather diverse. After separating the sample banks into three sub-groups, we find that the largest Chinese banks, China's global systemically important banks or G-SIBs, can gain positive improvements in their performance through diversification. The next group, the domestic systemically important banks or D-SIBs, shows a non-significant performance response to the shifting to diversified business. The significant under-performer is the group of China's non-systemically important banks or N-SIBs. The key factor that drives the performance differences lies in the banks' capability to reap the benefits of diversification through the learning-by-doing process. Other factors include size of the bank, regulatory differences and other factors such as moral hazard.

Chapter 4 puts the focus onto the issue of financial stability, and examines to what extent income diversification affects risk exposure of Chinese banks. Previous research indicates a linear relation between income diversification and risk, finding either a negative correlation that suggests banks should diversify, or a positive correlation that indicates banks should remain focused on core business. However, by adopting the first-differenced GMM estimator for the dynamic threshold panel data model, we unearth the evidence showing that in the Chinese case, the relation is not monotonously linear. Rather, the effects of diversification vary with time, sources of non-interest activities and measures of risk.

For the whole sample, there exists an inverse U-shaped relation between diversification level and risk. Income diversification will reduce bank risk only after the bank has passed a certain threshold of income diversification. This pattern of the relation seems to be driven mainly by the learn-by-doing effect in relation to the expansion of non-interest activities. After dividing the whole sample into three sub-groups, we find that, for G-SIBs which has a dominant position in the Chinese banking industry, business diversification has a significantly negative effect on the banks' both idiosyncratic risk and financial distress. However, for D-SIBs and N-SIBs, the relation exhibits an inverse U-shape, where in the early diversification stages the banks incur a discount and become less stable, but they become more stable after achieving a certain threshold level of diversification. It is plausible that these differences reflect the learning by doing effect and others such as different diversification strategies and risk preferences.

Results further reveal that, across different business lines, the diversification effects on bank risk are not uniform. Decomposing the revenue from non-traditional activities further into three sub-classes i.e. fee-based income, income from trading activity and other non-interest income, we find that where there is only a low level of diversification, both trading and other non-interest activities will lead to increased exposure to risk; only once the bank has achieved a certain diversification level will these activities start to provide diversification benefits that will lower bank risk. Activities that generate fee-based income will decrease bank risk for G-SIBs and increase risk for N-SIBs regardless of their diversification levels, while for D-SIBs there is an inverse result, positive for banks with a lower level of diversification and negative for more diversified banks.

We also examine the diversification effect across different types of risk. Evidence suggests that for G-SIBs and D-SIBs business diversification can reduce credit risks only when the banks have passed a certain threshold point, while for N-SIBs diversification cannot bring any improvement for credit risk regardless of diversification level. Similarly, the interest rate risk will be reduced only for highly diversified G-SIBs and D-SIBs. Finally, diversification will always reduce the liquidity risk, for all three banking groups. However, the reduction of the liquidity risk cannot fully offset the enhancement of the credit and interest rate risks. Therefore, it is necessary for banks to go beyond the threshold in order to obtain the risk-reduction benefits from diversification. This implies that to fully reap the benefits of risk reduction from income diversification, banks need to accumulate sufficient banking human capital and to establish an effective supervision system.

The objective of Chapter 5 is to analyse the efficiency implications of Chinese banks' shift to greater income diversification. To do so, we deploy a two-step approach. First, efficiency scores, both cost and profit, are calculated by stochastic frontier analysis using the method of within maximum likelihood estimation (WMLE). The stochastic frontier analysis is applied respectively to three sub-groups of Chinese banks. The evidence obtained indicates that during the sample period from 2005 to 2016, the average of both cost and profit efficiency scores exhibited an increasing tendency from 2005 to 2008 for the whole sample and then began to decline, reaching its nadir in 2010. Subsequently, the efficiency of Chinese banks improved steadily, to achieve a relatively high point after the global financial crisis. The three sub-groups each followed a similar trend to that of the overall banking sector.

In the second step, our investigation employs a dynamic Tobit model to examine the unobserved, time-invariant bank heterogeneity. We find that for the overall Chinese banking sector, income diversification has an efficiency-destroying effect. However, the effects vary across the banking groups. For Chinese G-SIBs, diversification has a significant harmful effect on both cost and profit efficiency. For D-SIBs, the effects are similar, but the discount is less. For N-SIBs, diversification has a positive effect on the efficiency level. The differences in empirical results could be explained by the additional overhead cost, inefficient cross-subsidization and moral hazard problems.

Further decomposing non-interest activities into three components, i.e. fee-based, trading and other activities, it is found that the diversification discount is generated from fee-based and other income activities, whereas trading activities can improve banks' efficiency level. The result is shaped by banks' internal business structure, as larger banks have an incentive to expand fee and other non-interest incomes which are highly volatile and less effective, but smaller banks are more likely to diversify towards less risky and more effective trading activities.

6.2 Implications of the Research

Implications flowing from this thesis have been multiple. The first of them concerns the development prospects of banks' diversifying into non-traditional activities. Our research shows that expansion of non-interest activities is beneficial for G-SIBs, the most important banks of the Chinese banking system. The performance enhancement can be attributed to the facts that they have accumulated huge assets, resources, technology, and human talent necessary to carry out financial innovations. Chinese D-SIBs are on the borderline, showing some sign of performance improvement, though not strongly significant. With further development of their non-interest business, they can be expected to learn to commend more innovative financial tools and develop better management skills. This implies that they have the potential to grow the diversification further. While N-SIBs show no gains in profitability in the sample period, their efficiency scores are shown to have improved steadily. With this, conducting of non-traditional business in the future can become profitable for them. All these indicates that business diversification by Chinese banks has the room to grow and develop in future.

Against this background, it is sensible for managers of G-SIBs to adopt a business expansion strategy that highlights efficiency enhancement because their efficiency scores are low. This can be achieved through using their institutional strength including extensive network of sub-branches to expand fee and commission activity. For small and medium-sized banks, i.e. D-SIBS and N-SIBs the sensible business strategy should focus on providing services through their close ties with customers and gradually develop non-interest financial services to reap the benefits of efficiency enhancement from the process. Structurally, given the fact that income from trading activity has played a particularly positive role in promoting banks' profitability and efficiency, managers of G-SIBs and D-SIBs should take steps to focus on trading business.

For the regulator, our research suggests a structured approach to supervision and regulation over Chinese banks' conducting of non-traditional business. The existing Chinese regulation over mixed banking business is modelled on the America's Financial Services Modernization Act of 1999, which is rather restrictive on income diversification. This should be reformed and it is necessary and desirable for the Chinese regulator to relax restrictions on banks' engagement in non-traditional business. The key area of reform action is to allow an enabling regulatory framework that releases banks from the existing legal constraints on their development of non-interest business.

Within this framework, the regulatory priority should be given to oversee the development of potential systemic risk that banks' shift to non-interest business may cause. The research shows that wide engagement of banks in income diversification would heighten the systemic risk. For one thing, as a result of business diversification, many banks are now doing very similar business. Their product structure thus becomes isomorphic, which makes them vulnerable to common shocks. For another, long-term business expansion consumes large amounts of capital, while banks' exposure to credit risk, interest risk and shadow banking risk would be on the rise, which reduce the banks to vulnerability further. In addition, relative to the income from traditional business, non-interest income is often instable. Then, with the growth of business diversification, the instability of non-interest income will also grow and the income instability can be transmitted from one bank to other banks. These would amplify the eventuality of systemic risks and the regulator should be wary of this and put the eventuality high in its monitoring radar. This is especially so for some high-leveraged and risky non-interest business requires.

On top of close supervision of systemic risk, the thesis suggests a structural approach to Chinese regulator's monitoring of financial stress and risk exposure of different banking groups. The inverse U-shaped relation between return and risk in the diversified business implies that some Chinese banks would initially have low performance with heightened risk and only after having passed some threshold would the situation becomes better. This threshold effect needs to be taken into consideration by the regulator in their policy design for supervising the banks, especially over the small and medium sized banks.

For the risk file of individual banks, the research has proved that engaging in non-interest businesses will reduce the risk exposure of G-SIBs. But this finding does not relieve G-SIBs from being put under sound supervision and regulation. Rather, considering that G-SIBs' efficiency scores are lowered by business diversification, the regulator should focus their supervision on the efficiency level of G-SIBs. For N-SIBs, evidence shows that they would see an increase in their risk exposure, so for these banks the regulator's main concern should be the dynamics of their risk exposure in relation to diversified business.

For particular types of risk, it is shown that income diversification can reduce liquidity risk for all three banking groups. But for credit risk and interest risk, while G-SIBs and D-SIBs can manage to reduce their exposure, there is no evidence that this would also be true for N-SIBs. Given this, the regulator should be particularly watchful for the levels of credit and interest risks of N-SIBs. They are relatively small by asset size, but are numerous in numbers and have an extensive customer base. Potential failure of these banks could have far-reaching social repercussions.

6.3 Limitations and Avenues for Future Research

This thesis attempts to investigate ongoing concerns in understanding the relations between banking diversification in China and its consequences amid the global trend of banks' shifting to non-traditional businesses. By offering a case study of income diversification of Chinese banks, this study brings closer to a better understanding of the effects of income diversification on profits, risks and efficiency in the Chinese bank industry and hence contributes to the long debate on the desirability and repercussions of banking diversification in recent decades. To advance the knowledge further in the field, it is sound and meaningful that the results and contributions of the thesis could be considered in the light of its limitations, which also provides the new avenues that could be explored in future studies. The limitations of the current study can be grouped as follows:

First, limitations due to the availability problem of raw data. This can be illustrated by the data problems when adopting the threshold dynamic panel estimator based on the first-differenced GMM method. The study applies this method in order to estimate the diversification-risk relation but is constrained by the severe data availability problem. But the methodology requires a balanced data set to satisfy the first difference process, which cannot be satisfied by raw data in China. In the empirical exercises in this thesis, we collate data of a sample of 40 Chinese commercial banks and the sample period chosen runs from 2005 to 2016. But in this sample period five of the banks did not exist before 2007. This leads the empirical study to reducing the observations by two years to begin in 2007, making the actual sample size relatively small.

With the passage of time, we expect the sample period in future can be extended, which dynamic threshold estimation. In that case, an augmented sample size will contribute to the accuracy of test results, and thus provide more accurate estimation.

Second, methods for dealing with missing values of data or incomplete data in the regression analysis. In response to the challenge posed by missing values of data or incomplete data, researchers have proposed several methods to estimating the regression model with missing or incomplete data (Abrevaya and Donald, 2017). One approach is to deploy the simulated moment of method that imputes the missing values conditional on the other available data (McFadden, 1989). Also known as the method of simulated moments, this method is a structural technique that generates simulated data from the economic model, and then matches their moments with those computed from the available data. Alternatively, one may use the indirect inference method (Smith, 1993; Gouriéroux et al., 1993). Using an auxiliary model whose parameters are to be estimated from either observed or simulated data, this approach chooses the parameters of the economic model so that these two sets of estimates are as close as possible. Compared to the method of simulated moments, the indirect inference is quite flexible as it allows use of any of the features of sample statistics as a basis for comparison of moments and data. Based on indirect inference, Gouriéroux, et al. (2010) propose a general method that can substaintially reduce bias related to T is small and fixed while N is large. Indeed, their approach is generic and works well for any values of N and T (Gouriéroux et al., 2010). This is particularly useful to explore these methods in future research as the Chinese market is less transparent than other mature one, and researchers often can have only relatively short panel data, which may cause biased estimation in the traditional GMM model.

Third, other types of diversification. This research has only considered one type, albeit the major one, of banking diversification, i.e. the income diversification. Future research should be extended to consider the development of some other types of diversification, for example geographical diversification, by Chinese banks. Currently, because of data availability, and that financial statements of regional branches are not available, research on other types of diversification is impracticable. When this improves and with increased availability and improved transparency of banking data in China, future research should make a wider coverage of examination of banking diversification.

Finally, alternative research strategy. Empirical analysis is not the only way to study diversification effects. In the Chinese banking sector, each bank has its own characteristics including institutional history, development courses, and relations with government and other institutions. These traits will a bearing on banks' diversification strategies and business performance. As such, future research can be advanced further to adopt a wide range of methods and modelling strategies, including case studies, in order to shed further lights on the effects of business diversification in the Chinese banking industry.

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APPENDIX

Table A1 Income diversification and banks' performance for G-SIBs, D-SIBs and N-SIBs by adopting dummy variables, 2005-2016

This table reports the two-step SYS-GMM dynamic panel estimation results with robust errors. Our dependent variables is return on assets (ROA). ROA (t-1) refers to the lagged dependent variables by one period. HHI_Dummy_GSIBs, HHI_Dummy_DSIBs and HHI_Dummy_NSIBs indicate three interaction terms by using the Herfindahl-Hirschman index multiply three dummy variables to catalogue G-SIBs, D-SIBs and N-SIBs. NIM indicates total interest income/total interest expenses. LTA is loans/total assets, and NON is the non-interest expenses/total assets. The Sargan test checks the null hypothesis, i.e., that the instruments used are not correlated with the residuals. AR (2) denotes the Arellano-Bond test for the 2nd-order autocorrelation in first differences. Figures in brackets present the standard error. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

	ROA
ROA (t-1)	0.452***
	(0.017)
HHI_Dummy_GSIBs	0.005**
	(0.002)
HHI_Dummy_DSIBs	0.002
	(0.001)
HHI_Dummy_NSIBs	-0.004***
	(0.001)
NIM	0.184***
	(0.012)
LTA	-0.004
	(0.001)
NON	0.009
	(0.031)
Constant	0.256***
	(0.053)
F-test	0.000
Sargan test	0.390
AR(2)	0.123
Observations	408

Table A2 Income diversification and banks' performance for G-SIBs, D-SIBs and N-SIBs by adopting dummy variables, 2005-2016

This table reports the two-step SYS-GMM dynamic panel estimation results with robust errors. Our dependent variables is return on assets (ROA). ROA (t-1) refers to the lagged dependent variables by one period. COM_Dummy_GSIBs, COM_Dummy_DSIBs, COM_Dummy_NSIBs, TRAD_Dummy_GSIBs, TRAD_Dummy_DSIBs, TRAD_Dummy_NSIBs, OTH_Dummy_GSIBs, OTH_Dummy_DSIBs and OTH_Dummy_NSIBs indicate nine interaction terms by using the fee and commissions, trading income and other income multiply three dummy variables to catalogue G-SIBs, D-SIBs and N-SIBs. NIM indicates total interest income/total interest expenses. LTA is loans/total assets, and NON is the non-interest expenses/total assets. The Sargan test checks the null hypothesis, i.e., that the instruments used are not correlated with the residuals. AR (2) denotes the Arellano-Bond test for the 2nd-order autocorrelation in first differences. Figures in brackets present the standard error. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

	Fee and Commissions	Trading Activities	Other Activities
	ROA		
ROA (t-1)	0.442***	0.336***	0.709***
	(0.016)	(0.073)	(0.028)
COM_Dummy_GSIBs	0.012**		
	(0.006)		
COM_Dummy_DSIBs	-0.011**		
	(0.006)		
COM_Dummy_NSIBs	-0.020***		
	(0.003)		
TRAD_Dummy_GSIBs		0.365***	
		(0.136)	
TRAD_Dummy_DSIBs		0.052*	
		(0.030)	
TRAD_Dummy_NSIBs		0.036**	
		(0.016)	
OTH_Dummy_GSIBs			-0.023
			(0.019)
OTH_Dummy_DSIBs			-0.064***
			(0.013)
OTH_Dummy_NSIBs			-0.035***
			(0.007)
NIM	0.165***	0.304***	-0.043***
	(0.013)	(0.063)	(0.015)
LTA	-0.005***	-0.003	0.001
	(0.001)	(0.003)	(0.001)
NON	0.096**	-0.069	0.447***
	(0.042)	(0.093)	(0.034)
Constant	0.342***	-0.005	0.050
	(0.041)	(0.138)	(0.044)
F-test	0.000	0.000	0.000
Sargan test	0.450	0.992	1.000
AR(2)	0.114	0.301	0.875
Observations	408	399	406

Table A3 Income diversification and banks' efficiency for G-SIBs, D-SIBs and N-SIBs by adopting dummy variables, 2005-2016

This table reports the results from Dynamic Tobit estimation. Our dependent variables are cost efficiency, which are estimated by stochastic frontier analysis. Cost_Effeiciny (t-1) refers to the lagged dependent variables by one period. HHI_Dummy_GSIBs, HHI_Dummy_DSIBs and HHI_Dummy_NSIBs indicate three interaction terms by using the Herfindahl-Hirschman index multiply three dummy variables to catalogue G-SIBs, D-SIBs and N-SIBs. Lerner indicates the Lerner index, NIM indicates net interest revenue over total earning assets, ETA refers to equity / total assets, CIR indicates the cost-income ratio. Figures in brackets present the standard error. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

	Cost efficiency
Cost_Effeiciny (t-1)	0.689***
	(0.164)
HHI_Dummy_GSIBs	-0.191**
	(0.086)
HHI_Dummy_DSIBs	-0.313***
	(0.107)
HHI_Dummy_NSIBs	0.001
	(0.093)
Lerner	-0.472***
	(0.078)
NIM	3.880***
	(0.876)
ETA	0.011
	(0.356)
CIR	-0.139***
	(0.049)
Constant	0.455***
	(0.175)
Log likelihood	12.464
LR test (p-value)	0.000
Observations	402

Table A4 Income diversification and banks' efficiency for G-SIBs, D-SIBs and N-SIBs by adopting dummy variables, 2005-2016

Dynamic Tobit estimation. Our dependent variables are cost efficiency, which are estimated by stochastic frontier analysis. Cost_Effeiciny (t-1) refers to the lagged dependent variables by one period. COM_Dummy_GSIBs, COM_Dummy_DSIBs, COM_Dummy_NSIBs, TRAD_Dummy_GSIBs, TRAD_Dummy_DSIBs, TRAD_Dummy_NSIBs, OTH_Dummy_GSIBs, OTH_Dummy_DSIBs and OTH_Dummy_NSIBs indicate nine interaction terms by using the fee and commissions, trading income and other income multiply three dummy variables to catalogue G-SIBs, D-SIBs and N-SIBs. . Lerner indicates the Lerner index, NIM indicates net interest revenue over total earning assets, ETA refers to equity / total assets, CIR indicates the cost-income ratio. Figures in brackets present the standard error. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

	Fee and Commissions	Trading Activities	Other Activities
	Cost efficiency		
Cost_Effeiciny (t-1)	0.454***	0.695***	0.498***
	(0.042)	(0.148)	(0.054)
COM_Dummy_GSIBs	-0.562***		
	(0.107)		
COM_Dummy_DSIBs	-0.332***		
	(0.108)		
COM_Dummy_NSIBs	-0.587***		
	(0.105)		
TRAD_Dummy_GSIBs		0.074	
		(3.265)	
TRAD_Dummy_DSIBs		1.377***	
		(0.468)	
TRAD_Dummy_NSIBs		0.558**	
		(0.234)	
OTH_Dummy_GSIBs			-0.281**
			(0.119)
OTH_Dummy_DSIBs			-0.063
			(0.903)
OTH_Dummy_NSIBs			0.466**
			(0.205)
Lerner	-0.294***	-0.331***	-0.297***
	(0.043)	(0.057)	(0.051)
NIM	1.938**	3.751***	3.254***
	(0.597)	(0.725)	(0.670)
ETA	0.896***	0.762**	0.564**
	(0.202)	(0.349)	(0.235)
CIR	-0.075*	-0.020	-0.011
	(0.045)	(0.055)	(0.049)
Constant	0.529***	0.245*	0.424***
	(0.051)	(0.146)	(0.060)
Log likelihood	589.446	338.381	561.330
LR test (p-value)	0.000	0.034	0.000
Observations	402	393	391