An Examination of the Chinese Banking System: Scale Economies, Cost Efficiency, Profitability and Financial Stability Modelling

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Abstract

This thesis is a timely and warranted examination of the scale and performance of the Chinese banking system for the years 2005 to 2015. Firstly, in light of the policy debate over "too big to fail", we examine evidence on the scale economies of banks, as well as technological change, to inspect whether industry consolidation is a rational objective for the larger banks in China to continue their asset growth. Secondly, utilising Stochastic Frontier Analysis, we construct a stochastic frontier cost function to examine the evolution of cost efficiency in the banking sector. Thirdly, considering the intense restructuring of banks over the study observation period, we explore the underlying variables that explain the profitability of Chinese banks. Finally, the driving factors that affect the resilience of Chinese banks are evaluated with the aim of maintaining the financial stability of the banking system.

During 2005 to 2015, significant economies of scale are found for large Chinese banks, driven by cost savings rather than by "too big to fail" considerations. Actually, greater cost economies are achieved by banks with lower credit risk, higher liquidity and "too big to fail" status. Therefore, recent policy recommendations that imply a limiting of bank size will place economic costs on large banks in China in the form of forgone scale economies. In addition, the technological progress that has been shaping the Chinese market provides justification for bank consolidation. We also observe that neglecting the costs of financial risks in the estimation can increase scale efficiency estimates for Chinese banks.

Overall, Chinese banks exploited higher levels of cost efficiency before the global financial crisis; thereafter, cost efficiency decreased. It is evident that stronger economic growth, lower inflation and exchange rate appreciation are able to improve the cost efficiency performance of Chinese banks. Linking cost efficiency to the profitability and financial stability of Chinese banks, we find that banks need to acquire superior risk management skills to realise greater cost efficiency with the aim of boosting bank profits. Nevertheless, a higher level of cost efficiency appears to hinder the solvency of banks through cost skimping behaviours. The involvement of Chinese

banks in shadow banking activities enhances the stability of banks to a very limited extent, and banks need to improve their competency to manage the associated costs in order to realise the profit-increasing effects of shadow banking operations. Asset growth and the utilisation of short-term wholesale funds are shown to strengthen banks' profit-generating ability and assist banks to become more stable. The Basel III capital requirements are seen to have affected the profitability and stability of "too big to fail" banks and "not too big to fail" banks differently. Moreover, banks' profitability is benefiting from a macroeconomic environment that features stronger economic growth, reduced inflation and a lower interbank offered rate; exogenous threats that weaken the resilience of Chinese banks mainly take the form of fluctuations in the interbank offered rate and exchange rate.

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List of Abbreviations

Agricultural Bank of China (ABOC)
Agricultural Development Bank of China (ADBOC)
Asset Management Companies (AMCs)
Bank for International Settlements (BIS)
Bank of China (BOC)
Bank of Tokyo Mitsubishi UFJ (BTMU)
China Banking Regulatory Commission (CBRC)
China Construction Bank (CCB)
China Development Bank (CDB)
China Yuan (CNY)
Data Envelopment Analysis (DEA)
Decision Making Units (DMUs)
Domestic Systemically Important Banks (D-SIBs)
Export-Import Bank of China (Exim)
Fixed Effects (FE)
Generalised Method of Moments (GMM)
Global Financial Crisis (GFC)
Global Systematically Important Banks (G-SIBs)
Industrial and Commercial Bank of China (ICBC)
Initial Public Offerings (IPOs)
Instrumental Variables (IVs)
Joint-Stock Commercial Banks (JSCBs)
Loan Loss Provision (LLP)
Merger and Acquisition (M&A)
Net Interest Margin (NIM)
Non-Performing Loans (NPL)
Ordinary Least Squares (OLS)
People’s Bank of China (PBOC)
Post Savings Bank of China (PSBC)
Return on Assets (ROA)
Return on Equity (ROE)
Royal Bank of Scotland (RBS)
Stochastic Frontier Analysis (SFA)
Too Big to Fail (TBTF)
Troubled Asset Relief Program (TARP)
World Trade Organization (WTO)

Chapter 1

Introduction

The association of the level of development of a country's financial sector with national economic growth has attracted great interest over the past few decades. There is a consensus that the real economy can be stimulated by developments within the financial system (see, for instance, Levine, 1997; Allen, Qian and Qian, 2005; Sturm and Williams, 2008; Luintel et al., 2008; and Koumparoulis, 2015). Despite these benefits, the establishment of a well-developed financial sector seems to be highly ambitious at best for transition economies – like China. Most studies concerning China highlight the significance of money supply and credit creation in the acceleration of economic growth, given that China is the world's largest bank-based economy[1] (e.g., Liang and Teng, 2006; Werner and Chung, 2010; and Beck et al., 2016). Overall, bank loans provided 68.6% of corporate funding in the year 2017, almost the double the figure for Japan and four times that for the US (KPMG, 2017). Accordingly, banks, as asset transformers, are the main source of funds for enterprises, are an integral part of the payment system, are the most important financial intermediary in the market, and have a significant role in the transmission of monetary policy in China (Hung et al., 2017).

In the last few decades, the Chinese banking system has undergone a series of dramatic and sustained transformations and developments, with the intention to generate more efficiency and reduce competitive inequalities in the domestic market. This process began in the 1980s with the introduction of three policy banks taking over the policy lending function from the four specialised commercial banks, thereby creating the so-called multi-tiered banking system in China[2], which has lasted through to the present day. Broadly speaking, those major banking reforms were:

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[1] In a bank-based economy, firms borrow heavily from banks. The capital market is underdeveloped and only a small portion of corporate financing needs are met via the issuance of securities (Liang and Teng, 2006).

[2] Figure 2.1 presents a graphical representation of the multi-tiered structure of the Chinese banking system.

- Setting up of the central bank, i.e., People's Bank of China, in 1994;
- Reconstruction of urban credit cooperatives as the rural and/or city commercial banks during the period 1996 to 1998;
- The operation of foreign banks under different licences[3];
- The establishment of non-state commercial banks;
- Credit allocation subjected to less government intervention;
- Liberalisation of interest, lending and deposit rates;
- Implementation of rigorous accounting standards and prudential norms; and
- Enforcement of a deposit insurance scheme from 2015.

Chapter 2 presents a detailed discussion of the financial reforms of the Chinese banking system; in brief, these efforts have considerably improved the performance of the Chinese banking industry and significantly promoted the growth of the real economy. Moreover, with the collapse of US giants and the retrenchment of large European banks after the global financial crisis of 2007-8, recently, the international presence of large Chinese banks has increased considerably[4] (Tan, 2016 and Wu and Shen, 2019). Since 2015, China has been running four of the world's five largest banks in terms of asset size (Feliba and Ahmad, 2021). The top spot is taken by the China's largest state-owned bank, Industrial and Commercial Bank of China, which in 2019 surpassed the total value generated by the whole of the British economy, with assets priced at US$3.62 trillion. Besides, in 2017, the Chinese banking sector beat the European banking sector (US$34 trillion) to be the world's largest banking system by asset size, in which the aggregated assets of the whole industry reached around US$39.9 trillion, up by 8.7% compared with the size for the previous year (Fang et al., 2019). This can be considered as a signal both of China's over-reliance on debt financing to stimulate its economic growth from the financial crisis in 2008 and of its increased leadership on a

[3] Various types of licences designate the scope of businesses that banks are permitted to participate in.

[4] Of particular note is the striking growth of the international footprint of the top 4 largest banks (by assets) in China. These banks are the Industrial and Commercial Bank of China (ICBC), the Bank of China (BOC), the China Construction Bank (CCB) and the Agricultural Bank of China (ABOC). ICBC and BOC operate in around 30 countries, while all these banks operate in Singapore, Hong Kong and South Korea (Turner, Tan and Sadeghian, 2012). In total, their foreign claims expanded roughly six-fold (increased from CNY2 trillion to CNY12.3 trillion) over 2007 to 2017 (Industrial and Commercial Bank of China, 2018).

global level[5].

Lately, the Chinese banking industry has transformed from a non-active acquisition sector to one where mergers have become normal in a bid to counteract intensive outside competition. There is a general view that the significant scale economies in banking have motivated the consolidation of banks' balance sheets (e.g., Tadesse, 2006; Hadad et al., 2013; Davies and Tracey, 2014; and Psillaki and Mamatzakis, 2017). However, the global financial crisis (GFC) brought to the fore a concern that the benefits of having larger banks might not outweigh the potential costs in terms of the risks to the financial system and broader economy of having banks that are 'too big to fail' (Beccalli, Anolli and Borello, 2015). As indeed the world banking system experienced during the GFC, large systemically important financial institutions like Lehman Brothers, Goldman Sachs and Merrill Lynch, were too big to fail. Not only was their collapse is extremely costly[6] to resolve due to their complexity, large global footprints and massive size, but also their failures transmitted systemic risk across the financial market and into the real economy[7].

In light of the severe negative consequences related to the (potential) failure of banks deemed to be too big to fail, as a response, policy makers have sought to implement

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[5] It might also reflect the decision of the Chinese government to enhance 'financial deepening', a term indicating the expansion of the financial sector with respect to the nation's gross domestic product (Tan, Floros and Anchor, 2017).

[6] The financial, economic and social costs associated with 'too big to fail' bailouts were demonstrated to be fairly high during the crisis. Taking the UK as an example, on 8th October 2008, the British government launched a bank rescue package totalling £500 billion as a response to the GFC. An aggregate total of £500 billion capital infusions was available for all UK incorporated banks and building societies in guarantees and loans. Specifically, an initial of £25 billion plus a further £25 billion were directed into the newly formed Bank Recapitalisation Fund to help troubled banks boost their market capitalisation; the central bank's Special Liquidity Scheme was equipped with £200 billion in the form of short-term liquid loans; and the remaining £250 billion was made available through a loan guarantee whereby the British government temporarily underwrote any eligible lending between UK banks.

[7] Indeed, as shown in the GFC, the severity of this crisis was exacerbated by the interconnectedness of systemic institutions via a mass of transactions and by a pro-cyclical de-leveraging process. Gradually, the market and public lost confidence in the solvency of these institutions. Then, the problems within the banking sector were promptly transmitted to the rest of the financial sector and the real economy, causing substantial contraction of credit availability (Cubillas, Fernández and González, 2017). In the end, the public sector had to step in with unprecedented injections of capital supports, liquidity buffers and guarantees.

constraints on banks by requiring more liquidity and capital (in line with the Basel III requirements) and also to restrict banks' operations in riskier areas – all of which curb bank size (Davies and Tracey, 2014). The aim of these supervisory considerations has been to limit implicit 'too big to fail' subsidies; yet, it seems to have largely overlooked the evidence that limiting bank size may induce economic costs for bigger banks in the form of foregone scale economies, which in turn results in a net social loss (see, for example, Hughes and Mester, 2013; Beccalli, Anolli and Borello, 2015; and Boyd and Heitz, 2016). To illustrate, Hughes and Mester (2013) argue that regulators should balance the need for safety of the financial system with the need to promote financial efficiency and dynamism when introducing regulatory reforms within the banking sector. Therefore, understanding the determinants of economies of scale – that is, whether the documented returns to scale are driven by technological progress or by subsidies given to institutions deemed to be too big to fail – is crucial, since policy recommendations will be different.

Furthermore, there is an increasing concern among policymakers about the probability of large Chinese banks repeating a Lehman-style collapse as their wholesale borrowing and shadow banking activities increase (IMF, 2017a). Such borrowing and operations are evidenced in the recent appearance of terms such as 'interbank loans', 'wealth management products' and 'shadow credits' in banks' financial reports, particularly those of large state-owned and joint-stock commercial banks (Allen et al., 2019). On the one hand, the utilisation of short-term wholesale funding and the involvement in shadow banking activities allows banks to strengthen their profitability performance[8] (Fang et al., 2019), while on the other hand, it implies a considerable increase in insolvency risk and systemic risk for banks under financial distress. In light of this stressful environment, and especially the large credit overhang[9] in China, the

[8] Recently, the profit margins of Chinese banks have under the pressure, given that the industry average of banks' return on assets ratio declined from 1.14% in 2010 to 0.95% in 2017 and return on equity ratio dropped from 21% in 2010 to 13.16% in 2017 (Fang et al., 2019).

[9] For China, the year-on-year (YoY) credit expansion has been continuously higher than the YoY growth of GDP since 2012. China has witnessed a dramatic increase in its debt to GDP leverage, up from 140% in 2008 to 253% in 2017. Over the loosening cycle in 2009, the ratio rose by 30ppt in a year, amid the CNY4 trillion stimulus programme (Ru, 2018).

evaluation of bank performance in an attempt to strengthen profits and risk control is necessary for maintaining the stability of the Chinese banking system and ensuring the well-functioning of the Chinese real economy.

As discussed, China has witnessed a range of financial reforms and deregulations which have affected the structure of its banking system. The business environment in which Chinese banks operate is increasingly risky and banks' asset structure is becoming more complex and more opaque. Consequently, examinations of the performance of Chinese banks in the context of recent developments are informative and add to the literature substantially; indeed, these developments mean that now is a very useful time for us to examine the risk management practices dominating the industry. If it is the case that a nation's economic development can benefit from a more efficient banking industry, then there is a public interest in both the banking system becoming more efficient and in evaluating its performance. Driven by all these considerations, this thesis:

- Examines the evidence on economies of scale in the Chinese banking industry, that is, scale economies, scale efficiency and technological change are estimated for sample banks.
- Investigates the sensitivity of bank scale economies to technological progress and/or 'too big to fail' status.
- Employs a clustering technique to allocate sample banks with similar funding and investment activities into the same natural clustering group – a more accurate empirical method for the identification of different business models in the banking sector.
- Studies the determinants of economies of scale for the Chinese banking industry so as to examine whether the diversification in bank business models, the 'too big to fail' status and risk-taking features affect the realisation of economies of scale.
- Explores the impacts of recapitalisation on Chinese banks.
- Assesses the performance of Chinese banks by means of operational research approaches and offers recent cost efficiency estimates of the Chinese banking

industry.

- Examines the determinants of bank profitability and financial stability in China. Specifically, through dynamic panel data regressions, the thesis examines how major bank characteristics (e.g., cost efficiency, expansion of shadow banking activities, utilisation of short-term wholesale funding and the 'too big to fail' status) and macroeconomic environment affect the performance of Chinese banks.
- Estimates the impacts of financial contagion (via a consideration of interbank exposures) on bank performance in China.

To address these topics, the each of the next four chapters presents an integral part of the research agenda with respect to Chinese banking, bank cost and profit performance, as well as risk-taking procedures.

1.1 Thesis Outline

Chapter 2 sets the contextual background of the Chinese banking industry and serves as the basis of the thesis, discussing issues related to our following empirical analysis of Chinese banks in Chapters 3 and 4. Chapter 2 presents an overview of the Chinese banking sector focusing mainly on the banking reforms and the main developments after the accession of China to the World Trade Organisation in 2001. In our analysis we focus on key trends concerning four key aspects of China's banking system previous to and covering our sample period 2005 to 2015: its structure; regulatory reforms; financial performance (e.g., total sector expansion, asset quality, earning competence and cost efficiency) and recent changes in business models and strategies.

In consideration of recent policy debates with respect to the 'too big to fail' status, following Beccalli, Anolli and Borello (2015), Chapter 3 investigates evidence of scale economies for Chinese banks and examines whether diversification in business models and risk-taking affect the realisation of economies of scale. We begin our analysis by estimating economies of scale and scale efficiency from a comprehensive set of cost specifications, each with different risk proxies. Recent research has suggested that systematic differences in risk among banks can substantially modify the way their costs vary with outputs, thereby producing biased estimates of bank scale economies when endogenous risk-taking is not considered in modelling bank production cost (see, for example, Wheelock and Wilson, 2012; Hughes and Mester, 2013; Bryce et al., 2015; and Delis, Iosifidi and Tsionas, 2017). Following this assumption, our cost estimation takes into account managers' risk preference by incorporating risk management variables in the specified cost frontiers.

Therefore, our analysis contributes to the Chinese banking literature as it is one of the few empirical studies to capture risk-taking in estimating bank cost. More importantly, unlike previous research (e.g., Dong, Hamilton and Tippett, 2014; Boateng, Huang and Kufuor, 2015; and Hou et al., 2018) that also recognising bank risk in constructing a cost function, our study includes three risk proxies separately and in different combinations. We then utilise the test developed by Li (1996, 1999) to test for differences across the various measures of scale efficiency derived in the first step to identify a best fitted cost specification. The estimates of technological change are also obtained based on the preferred cost specification with an aim to shed light on the logic of the ongoing trend for consolidation within the Chinese banking industry. Additionally, the full sample is divided into different groups according to two criteria – first, splitting the sample by asset size; and second, following Brown and Glennon (2000), segmenting banks based on their portfolio composition through a clustering approach.

With respect to the second grouping criterion, we estimate clusters in terms of portfolio mix, and hence allocate banks with similar production technology into the same natural clustering group. To the author's best knowledge, our study is the first to empirically evaluate differences in the production technologies among Chinese banks. Then, our empirical findings related to bank scale economies, scale efficiency and technological change are thoroughly analysed in line with the above-generated banking groups. Built on Hughes and Mester (2013), the policy debate on 'too big to fail' is addressed via the examination of whether the cost advantages provided by large-scale banking operations are due to technological scale economies or 'too big to fail' subsidies. Our findings add to the current banking literature by informing contemporary policy debate on proposed regulatory reforms that are likely to inhibit bank growth/size and shedding the light on the policy choice for banking authorities. Finally, utilising a dynamic panel data model, we evaluate the determinants of bank scale economies so as to investigate the influences of recent regulatory reforms (in accordance with Basel III requirements) on bank cost economies. The model is also conditioned on 'too big to fail' banks[10] in order to check the differences in performance between smaller banks and systemically important institutions.

In Chapter 4, with the background of the ongoing recapitalisation and banking reforms in China, we explore the effects of recapitalisation on banks, as well as examine the cost efficiency, profitability and stability performance of the Chinese banking sector. Our study starts with the inspection of the impacts of recapitalisation on Chinese banks by examining shadow return on equity (i.e., shadow price of equity) utilising a stochastic frontier cost function subject to a capitalisation constraint. To the best of our knowledge, only one published paper – Dong et al. (2016) – empirically examines this significant issue within the context of the Chinese banking industry, covering the period 2002 to 2011. Our analysis enriches the empirical evidence on this topic with more recent Chinese data. Then, we use Stochastic Frontier Analysis (SFA) models of Battese and Coelli (1995) and, following Simper et al. (2017), we incorporate the risk proxies identified in Chapter 3 in the frontier estimation to estimate cost efficiency scores for sample banks. Moreover, we model inefficiency as a function of a vector of exogenous (macroeconomic) factors which are expected to affect the distance of each tested bank from the estimated frontier. This constitutes a significant contribution as prior related research neglects the impacts of risk on efficiency estimation (e.g., Berger, Hasan and Zhou, 2009; Paradi, Rouatt and Zhu, 2011; and Dong, Hamilton and Tippett, 2014) and the impacts of exogenous determinants on efficiency.

In the next step of our empirical analysis, we turn our attention to the drivers of bank profitability and financial stability, and we investigate the earning ability and solvency

[10] Domestic systematically important banks are defined in our sample.

of Chinese banks in the context of the ongoing financial transformations in China. The yielded estimation results from above studies offer valuable information for managers to strengthen banks' soundness and profit-generating capacity. The comprehension of these contributing factors also offers insights to other emerging economies whose banking sectors are undergoing significant institutional and structural change. Our investigation contributes to the existing Chinese banking literature on profitability and stability determinants analysis in the following four aspects. First, our study focuses on the effect of actual cost estimates (i.e., cost efficiency scores) instead of commonly utilised cost-related financial ratios (e.g., cost to income ratio) on bank profitability and stability. Such a focus is distinct from that in other related research and consequently complements our knowledge from those studies. Lin and Zhang (2009) adopt the cost to income ratio as an efficiency proxy to examine how bank efficiency affect profitability. Similarly, Li and Zhang (2013) employ the ratio of operating expenses over total assets as a cost indicator in their bank profitability analysis. Tan (2016) utilises the overhead costs to total assets ratio to evaluate the correlation between bank efficiency and safety. However, these studies neglect the clear advantages in using estimated cost efficiency scores, as opposed to cost-related accounting ratios[11] (see a detailed interpretation of the rationale for cost efficiency scores are better efficiency proxies than the commonly employed accounting ratios on page 192 of section 4.2). Recognising the benefits of adopting cost efficiency score as an efficiency metric, our analysis use SFA models to estimate cost efficiency scores for sample banks and the scores yielded are then added into the second stage regression models of bank profitability and stability as one of the main determinants. This two-stage analysis contributes to current Chinese banking studies with a more comprehensive and robust framework to study the performance of Chinese banks.

Second, in recent years, an increasing number of studies have examined the variables that could affect bank profitability and stability within the context of Chinese banks (e.g., Shih, Zhang and Liu, 2007; Lin and Zhang, 2009; Li and Zhang, 2013; Zhang et al.,

[11] One such advantage is that the cost efficiency scores yielded from the frontier cost function estimation takes into account synchronously all aspects of bank performance, and can show a bank to be operating well even when individual financial performance ratios suggest the bank is inefficient.

2016; Tan, Floros and Anchor, 2017; and Umar and Sun, 2018). Nevertheless, to the author's best knowledge, there are no published empirical papers on Chinese banking that focus on the effects of shadow banking activities on bank profitability and solvency. Hence, our study fills this research gap by linking shadow banking activities to bank profits and soundness. Third, there is little research that investigates the potential links between short-term wholesale funding and performance for Chinese banks. One such empirical study is that by Qi and Yang (2017), which analyses how short-term wholesale funding affects Chinese banks' interest margins during the period 2000 to 2009. Our inspection of the effects of short-term wholesale funding on bank profits and solvency extends the literature by examining a dataset consisting of more recent Chinese data. Fourth, we explore the size-profitability/stability nexus, and its findings contribute to the existing banking literature by offering evidence for current regulatory discussions of downsizing in banking.

Chapter 5 concludes the thesis and analyses potential limitations and provides further research directions.

Chapter 2

The Chinese Banking Industry – Background Review

2.1 Chapter Summary

This chapter presents the contextual background with respect to the Chinese banking system as well as to the empirical analysis of Chinese banks in Chapters 3 and 4. This overview of the Chinese banking industry pays attention to the banking reforms and developments that have affected the estimates and results of the empirical analysis. The chapter is structured as follows. Section 2.2 offers an introduction. Section 2.3 summarises the major financial reforms that Chinese banks have undergone before and during our sample period (2005 to 2015). Both before and during sample period, China witnessed unprecedented reforms and structural changes across its financial system in an effort to deregulate and liberalise its financial services sector. Through these changes, China transformed itself from a government-driven single banking sector to a modern market-driven multi-tiered banking system. This multi-tiered banking structure is evaluated in section 2.4. Next, section 2.5 discusses banks' performance (e.g., total sector expansion, asset quality, earning capacity and cost efficiency) after the country's accession to the World Trade Organization (WTO) in 2001. In section 2.6, we discuss improvements in the capitalisation of Chinese banks and the implementation of Basel III capital standards. Section 2.7 examines recent changes in business models and strategies in banking in China. More importantly, we link the discussion in sections 2.5 to 2.7 to our hypothesis concerning the Chinese bank estimations presented in Chapter 3 and Chapter 4. This chapter ends with a brief conclusion in section 2.8.

2.2 Introduction

The People's Republic of China has a fairly young banking industry. Initially, the whole banking sector consisted of only a single bank, the People's Bank of China, which served as both the central bank and sole commercial bank, yet today China has a multi-tiered modern banking system (Yin et al., 2015). Accomplishing such significant structural changes took a set of unprecedented banking reforms over four decades. Throughout the sustained transition, together with liberalisation within the banking and financial system, there has been huge commercial success for the Chinese banking industry, with marked expansion in the sector's total size and profit. For instance, by the end of 2017, China had the world's largest banking sector (in terms of assets), with the total sector valued at US$39.9 trillion, up from US$4.8 trillion in 2005 (Fang et al., 2019). The net income of banking institutions in China in 2017 was US$345.6 billion (an increase of roughly 530% from US$54.5 billion in 2005), much higher than the net income of banking systems in most of the world's major economies, such as US$151.5 billion for the US and US$30.9 billion for Japan[12].

Since the global financial crisis (GFC), with the retrenchment of large European banks, Chinese banks have undertaken a bigger role in the world banking market[13], despite concerns about China's 'hard landing' and disruption from Fintech (see Tan, 2016; Wang and Wang, 2018; and Wu, Song and Chai, 2018). However, compared with its Western peers, the Chinese banking sector remains underdeveloped and burdened with poor asset quality (Zhang et al., 2016; IMF, 2017). The earning capacity of Chinese banks has also been under pressure in recent years, mainly because the liberalisation of interest rates significantly lowered banks' interest income, but also because of the quick rebound in non-performing loans (NPLs)[14] (Tan, Floros and Anchor,

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[12] Data reported by S&P Global Market Intelligence Platform and CEIC Data.

[13] By the end of 2017, China had overtaken the eurozone as world's largest banking system in terms of assets (with the total sector valued at US$39.9 trillion), a sign of the country's increased influence in world finance (Fang et al., 2019). Moreover, as of mid-2018, the Chinese banking industry accounted for 7.1% of total cross-border bank lending in the world banking market. It is ranked at the world's 5th largest by market share (7.1%) in global cross-border lending, with the Japanese banking (15.4%), US banking (11.3%), French banking (11.3%), and UK banking sectors (9.5%) coming in at the world's 1st, 2nd, 3rd, and 4th largest, respectively (BIS, 2020).

[14] See Figure 2.6 and see section 2.5 for a more detailed interpretation of this issue.

2017). More importantly, a series of financial reforms, the experience of the GFC and the post-crisis market environment have had substantial effects on Chinese banks. In order to adapt to their new operating landscape, Chinese banks have been adjusting their business models and strategies. Specifically, major banks took the initiative and have been making aggressive adjustments to their balance sheet structure (e.g., increasing the portion of short-term wholesale funding), scope of operations (e.g., participating in a variety of shadow banking activities) and their cost base (Hou et al., 2018; BIS, 2018). Meanwhile, in terms of banking regulation, the Chinese regulatory authorities have come to focus on the surveillance and prevention of financial risks; this risk control centres on liquidity and systemic risk and the asset quality of Chinese banks.

2.3 A Brief Review of Three Stages of Banking Reform

The modernisation of the Chinese banking was initiated with the implementation of a centrally planned economy, which began with the foundation of 'modern' China in 1949 (Yin et al., 2015). As Franklin, Qian and Qian (2007) commented, during this period *"China's financial system consisted of a single bank, the People's Bank of China, a central government owned and controlled bank under the Ministry of Finance, which served as both the central bank and a commercial bank, controlling about 93% of total financial assets of the country and handling almost all financial transactions between 1950 and 1978. This period could be characterised as a typical socialist banking system"* (page 6). Accordingly, the Chinese banking system was originally dominated by one single entity and was fully controlled by the government up until 1978; thereafter, a series of deregulations aimed at liberalising and restructuring the banking sector.

That is, since 1979, with China's implementation of market economy transformations, the Chinese banking system has been subject to three stages of reform (see Berger, Hasan and Zhou, 2009; Dong, Girardone and Kuo, 2017; and Ye, Zhang and Dong, 2019). The period from 1979 to the early 1990s can be thought of as the first stage of banking reform in China[15]. That is when the four large state-owned banks – known as the 'Big Four' – were created and took over the commercial banking function from the central bank, the People's Bank of China (PBOC). Those four banks are: the Industrial and Commercial Bank of China (ICBC), the Bank of China (BOC), the China Construction Bank (CCB) and the Agricultural Bank of China (ABOC). In addition, several new commercial banks, known as 'joint-stock' banks, also entered the banking industry in the mid-1980s to increase competition.

The second stage of reform began in the early 1990s and ended with China's accession to the WTO in 2001[16]. This wave of bank transformations was primarily aimed at promoting market-oriented practices on the part of state-owned banks. Three 'policy banks' were established in 1994 to separate policy-directed lending from the state-owned banks. The government injected capital to the Big Four in 1998 (the total value amounted to US$32.5 billion) in an attempt to repair the balance sheets of the state-owned banks. In addition, local provincial governments were allowed to set up 'second tier' city commercial banks through the merging and restructuring of more than 5,000 urban cooperative banks. The Central Bank Law (18th March 1995) and Commercial Banking Law (promulgation date 10th May 1995) were enacted to standardise banks' operations, improve bank governance and enhance the independence of the PBOC and commercial banks. Additionally, the PBOC allowed foreign banks to perform a basic level of operations in the domestic market (although this was not enacted through the former laws) even though there were strict restrictions in place until the entry of China to the WTO in 2001.

Dong, Girardone and Kuo (2017) suggest that "*the third period [of banking reform] includes the early 2000s up until the most current years when speed of reforms accelerated with the aim of enhancing the reputation and the international*

[15] Based on discussions with respect to three stages of banking reform in China in Berger, Hasan and Zhou (2009), Dong, Girardone and Kuo (2017) and Ye, Zhang and Dong (2019), our study summarises the major reforms that banks have undergone during each stage in this section.

[16] "The People's Republic of China may accede to the Marrakesh Agreement Establishing the World Trade Organization on the terms and conditions set out in the Protocol annexed to this decision." 10 November 2001. World Trade Organization (WT/L/432).

competitiveness of the Chinese banking sector" (page 213). Since 2001, in response to its accession commitments to the WTO, China has gradually eliminated formerly strict restrictions on the operation of foreign banks so as to open up its banking system to foreign competitors. To illustrate, foreign banks were permitted to provide local currency services – including deposit-taking, loans, and other services – to Chinese corporate clients from 2003, and to individual customers from 2006[17] (WTO WT/L/432, 2001). The WTO accession also led major Chinese banks to widely adopt international accounting standards (from 2006), and thereby brought transparency to the industry as well as brought banks' accounting information into the scope of international use and communication.

Moreover, the third stage of reform saw the foundation of the China Banking Regulatory Commission (CBRC) in April 2003 to take over the PBOC's supervisory functions. Since then, the CBRC has become the central regulatory authority in the Chinese banking system, focusing on crucial areas such as corporate governance, accounting standards and requirements for loan classification, risk management and capital adequacy (He, 2012). Other major reforms implemented during this stage include: (i) a series of banking recapitalisation programmes such as government capital injection and public listing of banks on stock exchanges[18]; (ii) the establishment of four asset management companies to acquire and liquidate NPLs from the Big Four; (iii) the introduction of foreign strategic investment; (iv) the introduction of Basel regulations and a deposit insurance scheme to commercial banks; and (v) the creation of private banks as well as internet banks.

It can be noted that these changes took China four decades to implement, in what amounts to a thorough set of unprecedented banking reforms and opening up of the banking market. For a list of major reforms, see Table 2.1. In general, these reforms

[17] Due to deregulation, foreign banks expanded their presence in the domestic banking market. The percentage of foreign banks among total banks for China increase from 6% in 2006 to 18% in 2008, 21% in 2010 and to 20% in 2013 (data reported by CEIC Data).

[18] Most of the Chinese listed banks chosen to list on Shenzhen Stock Exchange, Shanghai Stock Exchange and Hong Kong Stock Exchange. See section 4.2 for a more detailed discussion of bank recapitalisation in China.

can be considered as triumphs for China, resulting in three decades of 10% compound annual real GDP growth (Dong, Girardone and Kuo, 2017)[19]. These reforms also contribute to a significant improvement in the size and performance of Chinese banks. For instance, the total assets of Chinese banks have tripled during the last three decades, reaching US$39.9 trillion by the end of 2017, an increase of roughly 2117% from 1997. The ratio of bank assets to GDP rose from 90.47% in 1997 to 174.54% in 2017[20]. In addition to the asset growth, the financial performance (e.g., capitalisation and asset quality) of Chinese banks has been strengthened markedly. For a more detailed analysis of this, see sections 2.5 and 2.6. More importantly, these reforms could be characterised as the change from a specialised to a commercial banking sector with the transition from a single-bank banking system to a multi-tiered banking system that is composed of a central bank and various bank institutions with distinct ownership structures and some large banks. We next discuss the multi-tiered structure of the contemporary Chinese banking industry.

[19] In addition, by the end of 2010, China had become the world's second largest economy, with Japan surrendering its 42-year-old ranking after its economy shrank in the final month of 2010 (Zhang, Wang and Wang, 2012).

[20] Data reported by S&P Global Market Intelligence Platform and CEIC Data.

Table 2.1: Major banking reforms and policy steps in China over the last four decades.

Period	Banking reforms and important policy steps
1978-1984	PBOC separated from Ministry of Finance; State-owned commercial banks established; PBOC's role as a modern central bank established by State Council and commercial activities transferred to the state-owned commercial banks.
1985-1995	Establishment of the first joint-stock bank and urban credit cooperatives; Creation of the policy banks; Commercial Bank Law promulgated; Central Bank Law passed.
1996-2003	Creation of interbank market; Start foreign currency business by commercial banks; Transformation of state-owned banks into 'commercial banks without direct administrative controls'; Credit allocation based on market principles rather than quotas under the government's credit plan; Transfer bad debts of state-owned commercial banks to four asset management companies; Accession to World Trade Organization (WTO), foreign banks to be treated equally as domestic banks within 5 years; Foreign banks allowed to provide foreign currency services to Chinese residents; New bank regulator (China Banking Regulatory Commission or CBRC); CBRC encourages foreign banks to buy stakes in Chinese banks; Law of Banking Regulation and Supervision adopted; Urban credit cooperatives transformed into city commercial banks, some rural cooperatives transformed into rural commercial banks.
2004-2008	Foreign banks allowed to provide local currency services to Chinese enterprises in designated cities; CBRC requires banks to fully provision non-performing loans and maintain minimum 8% capital ratio, fully binding as of 2007; CBRC strengthens on-site examinations and monitoring of large exposures, and introduces risk-based supervision; Banks encouraged to list on stock exchanges; five-tier loan classification made fully compulsory for all banks; By December 2006, China has opened its banking sector fully to foreign banks and eliminated geographical and client restrictions; Postal Savings Bank of China established; the reserve requirements ratio (RRR) is raised to 17.5% from 6% during 2003-2008; RRR reduced to 15.5% for large banks and to 13.5% for small banks in Q4 2008.

Period	Banking reforms and important policy steps
20009-now	Accession to Basel Committee on Banking Supervision; the implementation of Basel II and later Basel III regulatory policies to commercial banks; In addition to imposing minimum capital and liquidity requirements in line with Basel III standards, CBRC requires banks to hold a minimum liquidity ratio (liquid assets/current liabilities) of 25%, a minimum provision coverage ratio (provisions/non-performing loans) of 150% and an additional capital conservation buffer of 2.5%; Creation of private banks and internet banks; Establishment of the deposit insurance scheme.

Source: Berger, Hasan and Zhou (2009), Dong, Girardone and Kuo (2017) and Ye, Zhang and Dong (2019)

2.4 Current Banking Structure

The series of structural changes described above were an attempted to create a sound, profit-driven and competitive banking system. Gradually, the banking system changed to one that included institutional categories where each bank type initially worked in separate market segments and had clearly delineated functions. To date, as exhibited in Figure 2.1, the Chinese banking system presents a structure with the following institutional arrangements (Almanac of China's Finance and Banking, 2017):

- The People's Bank of China and China Banking Regulatory Commission respectively serve as the central bank and as the specialised regulator of banks in China;
- There are large state-owned commercial banks and three policy banks;
- There are medium-sized and small joint-stock commercial banks, foreign banks, city and rural commercial banks; and
- There are other types of banks, such as internet and private banks.

The PBOC operates at the top tier of the banking industry, functioning as the central bank[21]; it is subject to supervision by the State Council (National People's Congress) and chief administrative authorities (e.g., Ministry of Finance). Following the State Council's decisions in the 1995 Central Bank Law establishing the PBOC, it was given executive powers modelled on its US counterpart, i.e., the Federal Reserve System (Fu and Heffernan, 2009). Accordingly, the organisation became responsible only to the State Council, so as to free the PBOC from interventions of city governments or any other financial institutions and ensure an independent monetary policy.

In particular, the Central Bank Law (Article 4) states that the PBOC operates the following functions:

[21] The PBOC is one of the biggest central banks in the world, with US$3.02 trillion in foreign-exchange reserves (excluding Hong Kong) in 2016. The ratio of central bank assets to GDP for China has fluctuated from 3.85% in 1985 to a high of 6.10% in 1991 and a low of 1.33% in 2006. During the GFC, this ratio stood at 5.19% but thereafter decreased year on year to end at 2.07% in 2016 (Beck et al., 2019).

1. Drafting and enforcing relevant laws, rules and regulations that are related to fulfilling its functions;
2. Formulating and implementing monetary policy in accordance with law;
3. Issuing the Renminbi and administering its circulation;
4. Regulating financial markets, including the inter-bank lending market, the inter-bank bond market, foreign exchange market and gold market;
5. Preventing and mitigating systemic financial risks to safeguard financial stability;
6. Maintaining the Renminbi exchange rate at an adaptive and equilibrium level, holding and managing the state foreign exchange and gold reserves;
7. Managing the State treasury as fiscal agent;
8. Making payment and settlement rules in collaboration with relevant departments and ensuring normal operation of the payment and settlement systems;
9. Providing guidance to anti-money laundering work in the financial sector and monitoring money-laundering related suspicious fund movement;
10. Developing statistics system for the financial industry and being responsible for the consolidation of financial statistics as well as the conduct of economic analysis and forecast;
11. Administering the credit reporting industry in China and promoting the building up of credit information systems;
12. Participating in international financial activities in the capacity of the central bank;
13. Engaging in financial business operations in line with relevant rules; and
14. Performing other functions prescribed by the State Council.

Chinese commercial banks can be classified into four types in terms of their ownership structure: (1) state-owned commercial banks, which nearly 70% of the equity is owned by the Chinese central government and Ministry of Finance; (2) joint-stock commercial banks whose major shareholders are financial holding companies, local governments or leading conglomerates in one or more specific sectors; (3) city and rural commercial banks, which primarily are owned by local governments and local enterprises; and (4) foreign commercial banks, which typically present a joint venture capital structure or a fully foreign-controlled ownership structure (Almanac of China's Finance and Banking, 2017).

As previously stated, over the period of 1978 to 1984, four stated-owned commercial banks, the 'Big Four', were created to take over the commercial banking functions (e.g., deposit-taking and lending) from the PBOC, and built the foundation of the current Chinese banking system. One key feature of the Chinese banking sector is that it is highly concentrated (i.e., dominated by stated-owned commercial banks). In the early 1990s, the Big Four held almost 91% of total deposits and 90% of total loans of the entire banking system. After 20 years of financial reforms, especially with respect to entry to the WTO and bank initial public offerings (IPOs), by the end of 2016, the market share of state-owned banks in the total banking assets had dropped considerably from around 89% in 1995 to 41% (see Figure 2.2). Such a downward tendency can also be attributed to the increased competition and more aggressive growth strategy of smaller banks (Ye, Zhang and Dong, 2019). However, they still held 52.1% of deposits and 46.5% of loans by the end of 2016; and the now stated-owned commercial banks are still "too big to fail" due to their huge size and oligopolistic roles in the real economy (Wu, Song and Chai, 2018).

It should be noted that state-owned commercial banks remained as the Big Four until 2005, when Bank of Communication restructured and transformed from the largest joint-stock bank to the fifth largest state-owned bank. Then it was demoted to 6th largest in 2016 when Postal Savings Bank of China became the 5th largest[22]. Generally, state-owned commercial banks are faced with issues around tight government controls (e.g., the government would dictate the type of services, products and loans that banks offer) due to their ownership character[23] and are tightly regulated by the PBOC and

[22] In December 2015, Postal Savings Bank of China sold 17% of its equity to 10 international investors for US$7 billion. In September 2016, it undertook an IPO of US$7.4 billion, where cornerstone investors (usually government-linked investors that have to hold onto shares for a minimum of 6 months) – committed US$5.9 billion to the deal before its launch, giving them around 80% of the offering (Lockett, 2016).

[23] As of December 2016, nearly 70% of the equity of the Big Four as well as Bank of Communication are owned by the Chinese central government and Ministry of Finance, and roughly 69% of the equity of

CBRC since they are the systemically important financial institutions in China (Chen et al., 2014). Furthermore, these banks have historically been burdened by high levels of non-performing loans, which in the past has contributed to the notion that the Chinese banking system was "bankrupted" over the early 2000s (Lu, Thangavelu and Hu, 2005).[24]

Several joint-stock commercial banks (JSCBs) with a national presence were created in 1987. The China Merchant Bank and Bank of Communication (later restructured as a state-owned bank) were the first to enter the Chinese banking market (García-Herrero, Gavilá and Santabárbara, 2009). The market share of JSCBs then increased over the decade, reaching 19% of total Chinese banking assets by the end of 2016. There are currently 12 JSCBs. Unlike the state-owned commercial banks, they normally operate without extensive branch networks and receive capital and funding support from state-owned enterprises. Due to less interference from the government, JSCBs are usually market share winners and more aggressive and competitive in the financial services market (Lin, Sun and Wu, 2015). JSCBs are indeed typically more responsive to market conditions (they are primarily market-oriented) and have exemptions from historical policy lending regulations. They are licensed to provide a wide range of banking services, one of which is financing small and medium-sized enterprises, an area in which the state-owned commercial banks have traditionally been weak. Huang et al. (2017) note that on the basis of JSCBs' ownership structure, they can be categorised into three different types[25]:

1. banks with a sectoral background;
2. banks with a local government background; and
3. banks with a financial holding company background.

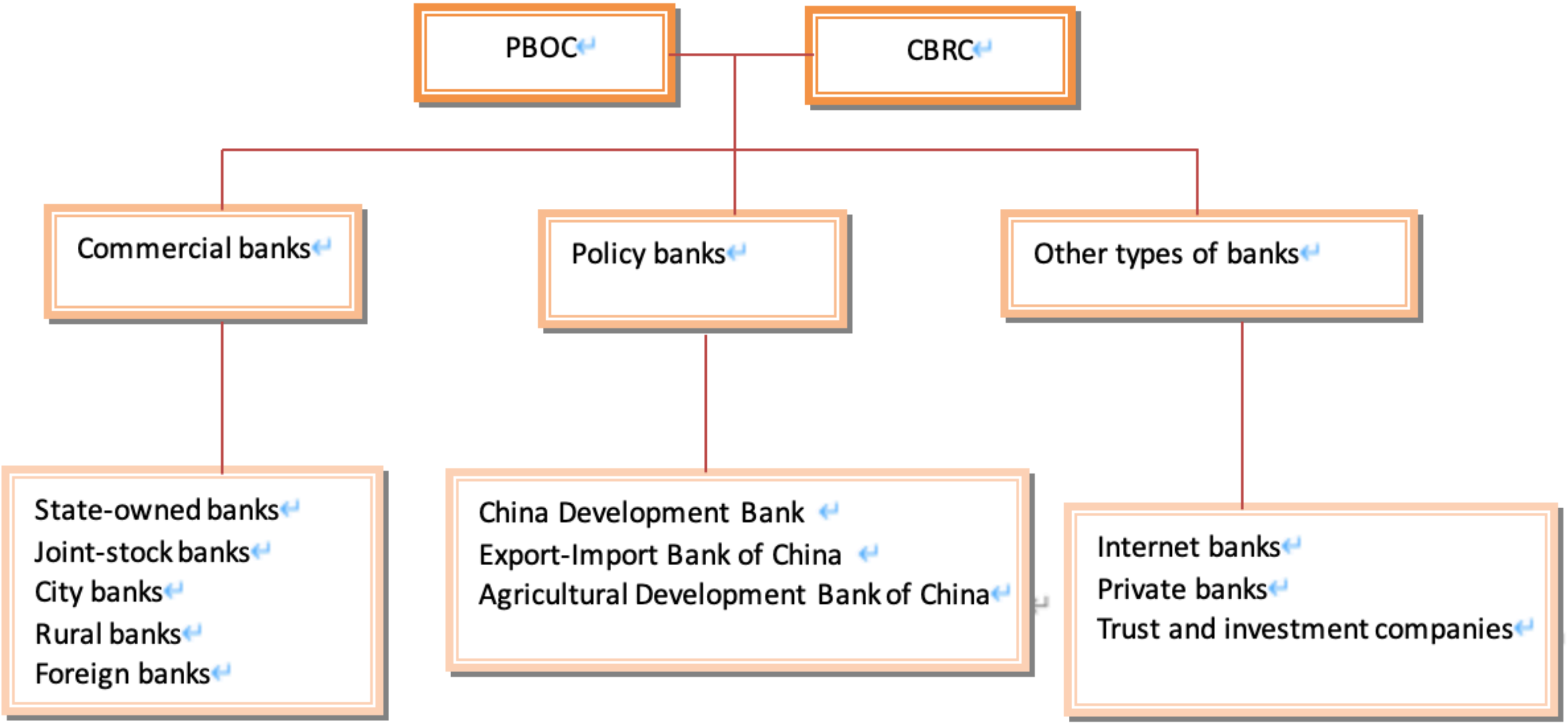
Postal Savings Bank of China are owned by the State Post Bureau (Garnaut, Song and Fang, 2018).

[24] For a more detailed discussion on bad debt problems of the state-owned commercial banks, see the following section 2.5.

[25] The banks with a sectoral background are those JSCBs whose major shareholders are leading conglomerates in one or more specific sectors, one of the main operating incomes of these banks comes from the income earned by the financial services and products banks provide for the sectors they serve. The banks with a local government background refer to the group of JSCBs whose major shareholders are local governments, whereas the banks with a financial holding company background denotes JSBs who are a subsidy of a financial holding company. Below Table 2.2 lists a few bank examples across the above three different categories.

Each category has distinct strengths and weaknesses (see Table 2.2) and each has distinct competitive characteristics.

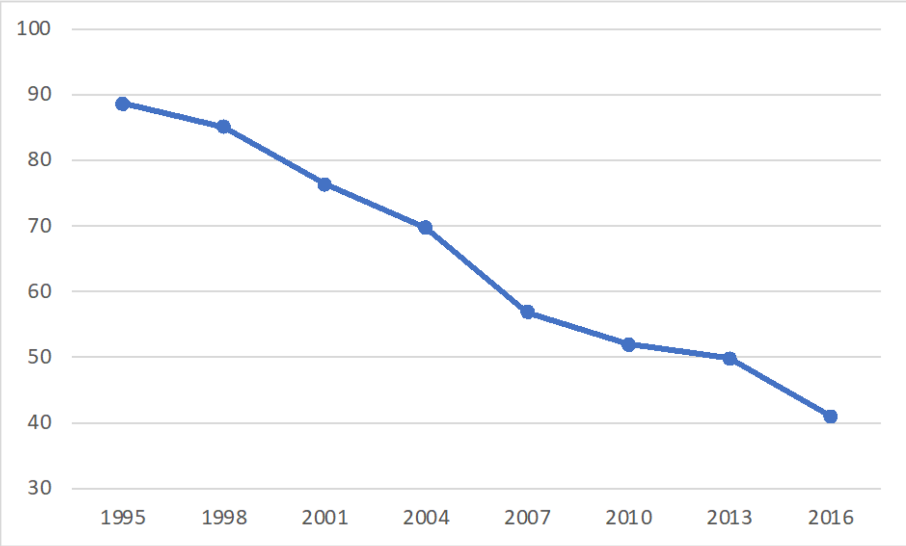
Figure 2.1: The multi-tiered structure of the Chinese banking system.



PBOC: People's Bank of China, CBRC: China Banking Regulatory Commission.

Source: Almanac of China's Finance and Banking (2017)

Figure 2.2: The asset market share of state-owned commercial banks (%).



Source: CBRC and S&P Global Market Intelligence Platform

Table 2.2: Categorisation of joint-stock banks by shareholder background.

Category/example banks	Strengths	Weaknesses
Sectoral background:		
CMB - Shipping and transportation HXB - Steel and infrastructure	Strong commercial orientation driven by corporate shareholders; More aggressive corporate culture	Concentrated sector risk; Risk of related party transactions and hidden non-performing loans by “evergreening loans”
Local government background:		
SPDB - Shanghai city CIB - Fujian province GDB - Guangdong province	Strong relationship with corporate clients owned or supported by local government; Low-cost funding from local government deposits; Clear “home base” advantage	Subject to the open-mindedness and influence of their local government; Overlap with their city commercial banks; Concentrated geographical risk
Financial holding company background:		
CNCB - China CITIC Group CEB - China Everbright Group	Strong brand name from the parent co.; Platform for cross-selling and expanding into other financial services (e.g., brokerage, insurance, trusts, etc.)	Lack of sense of urgency and competitiveness – similar to state banks; Lack of clear market positioning

CMB: China Merchants Bank, HXB: Hua Xia Bank, SPBD: Shanghai Pudong Development Bank, CIB: Industrial Bank, GDB: China Guangfa Bank, CNCB: China CITI Bank, CEB: China Everbright Bank.

Source: Huang et al. (2017)

With respect to city commercial banks and rural commercial banks, both are primarily controlled by local governments as well as local enterprises. The former banks were established by consolidating urban credit cooperatives and the latter by restructuring and consolidating rural credit cooperatives within a particular region. The setting up of rural commercial banks began in 2004 (see Lin and Zhang, 2009). As the Jia (2009, page 79) states, "*they have identified a clear market niche and developed a strategy of staying focused on localities of incorporation, serving small and micro enterprises, and tailoring their products and services to seek differentiated competition with large commercial banks*". Typically, city commercial and rural commercial banks operate only in one city or region, although some city commercial banks with strong financial performance have expanded cross-regionally in recent years.

For example, the Bank of Shanghai was the first to be allowed by the PBOC to establish a branch in Beijing, in 2005. Henceforth, the number of city and rural commercial banks seeking to grow their geographical presence has increased; however, most attempts fail due to the lack of local-government support and business contacts in the new region. It should be noted that the financial performance of these institutions depends mostly on their relationships with local governments and the economic growth of the region in which banks operate. In addition, these banks tend to be unevenly distributed across the mainland: they operate more in the developed south-east regions than in the less well-developed western regions. They are more likely to be concentrated in the city where the bank was founded. As of December 2016, they held around 21% of total banking assets.

As indicated previously, China's accession to the WTO in 2001 represented the occasion on which the Chinese government agreed to open up its banking system. In December 2006, the CBRC permitted nine foreign banks to start their preparatory work for launching local branches in China (Yin et al., 2015). Currently, more foreign banks have been able to incorporate locally in China; as such, the banking competition could benefit from the increasing presence of foreign banks. Generally, Garnaut, Song and Fang (2018) point out that there are four models for foreign banks to enter the domestic banking market:

1. acquiring a minority share in an existing bank;
2. establishing a representative office or bank branch[26];
3. creating a joint venture with a domestic bank[27]; and
4. setting up a fully foreign-owned bank[28].

In China, the latter three types of foreign venture are considered to be foreign banks subject to domestic rules and regulations governing them. By the end of 2016, foreign banks had only 1% of the national market share, indicating a rather limited foreign participation in the Chinese banking industry.

Policy banks were created in 1996 to ease government-directed spending functions from state-owned commercial banks in order to encourage market practices for state-owned commercial banks. These were the China Development Bank (CDB), the Export-Import Bank of China (Exim) and the Agricultural Development Bank of China (ADBOC). These three institutions operate in the role of policy financing and generally accumulate capital by issuing treasury bonds to commercial banks. Each policy bank has a different sectoral focus. Specifically, CDB issues loans mainly to support the infrastructure construction in transportation, telecommunications, energy and resource development in the middle and western parts of China, as well as the technology renovations of some enterprises. Exim promotes and guarantees export and import credits. ADBOC focuses on supporting forestry, water conservation and the purchasing and storage of agricultural and side-line products (Lin and Zhang, 2009). They together had approximately 10% of total banking assets by the end of 2016.

Other than the commercial banks and policy banks discussed above, the remaining 8% market share belongs to 'other' types of banks, such as internet banks[29], private

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[26] For example, Standard Chartered, Deutsche Bank and Singapore's DBS.

[27] HSBC in 2004 took a US$1.7 billion or 20% investment in Bank of Communications (one of the first such entries by a foreign bank). It was "*a highly structured joint-venture arrangement to cooperate in credit cards, including distribution of co-branded cards on nationwide basis*" (Hope and Hu, 2006, page 80).

[28] For example, HSBC operated 198 own-brand branches in 2014 across China and generated US$978 million in pre-tax profits (HSBC, 2015).

[29] For example, WeBank and MyBank.

banks[30] and trust and investment companies[31].

2.4.1 Regulatory Structure

As indicated in section 2.3, following China's entry to the WTO, the CBRC was established in 2003 (under the direct administration of the State Council) to take over the supervisory functions of the PBOC[32]. In general, the founding of the CBRC was cited as a milestone and a step towards creating an effective and robust banking regulatory system in China (see Fu and Heffernan, 2009; He, 2012; and Borst, 2015). As He (2012) suggests, "*by separating banking regulatory supervision and monetary policy, and creating the CBRC, China took a significant step toward pursuing a better and stronger banking regulatory framework. The major justification for divorcing the regulatory activities from the PBOC was that, in engaging in monetary, as well as regulatory activities, the PBOC would experience conflicts of interest caused by the interaction of micro (regulatory) and macro (monetary) policies*" (page 386). Since then, China has consolidated its supervisory institutional structure by developing specialised regulators[33].

As the principal regulator of the Chinese banking system, the CBRC's main functions include[34]:

1. Regulating and supervising the banking sector in China in accordance with laws and regulations, ensuring the legal and stable operation of banking institutions;
2. Formulation of supervisory policies governing banking institutions;

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[30] For instance, Shanghai Huarui Bank and Wenzhou Minshang Bank.

[31] For example, Guangdong Overseas Chinese Trust & Investment Corporation. The role and number of this type of institutions has been fading over time and they have diversified away (García-Herrero, Gavilá and Santabárbara, 2009).

[32] While banking regulatory power has been detached from the PBOC, as was mentioned on page 30, it does still supervise the payment system, interbank markets, as well as the credit information system and settlement system.

[33] Overall, in China, the banking regulatory framework has four tiers: (1) laws enacted by the National People's Congress; (2) ordinances enacted by the State Council; (3) regulatory policies issued by the CBRC; and (4) guidance notices and rules set by the CBRC.

[34] CBRC (2017b).

3. Authorisation of the establishment, changes to, termination of and business scope of banking institutions;
4. On-site examination and off-site surveillance of the banking system, and enforcement of actions against rule-breakers;
5. Establishing risk monitoring, control, assessment and early-warning mechanisms for the banking sector;
6. Compilation and publishing of statistics and reports on the industry in accordance with relevant regulations;
7. Provision of proposals on the resolution of problem deposit-taking institutions in consultation with relevant regulatory authorities;
8. Responsibility for the administration of supervisory boards of the major state-owned banking institutions;
9. Providing guidance for and monitoring the work of local financial regulatory authorities;
10. Engaging in the activities of international banking organisations, including the international regulatory standard-setting work for the banking sector; and
11. Other functions delegated by the State Council.

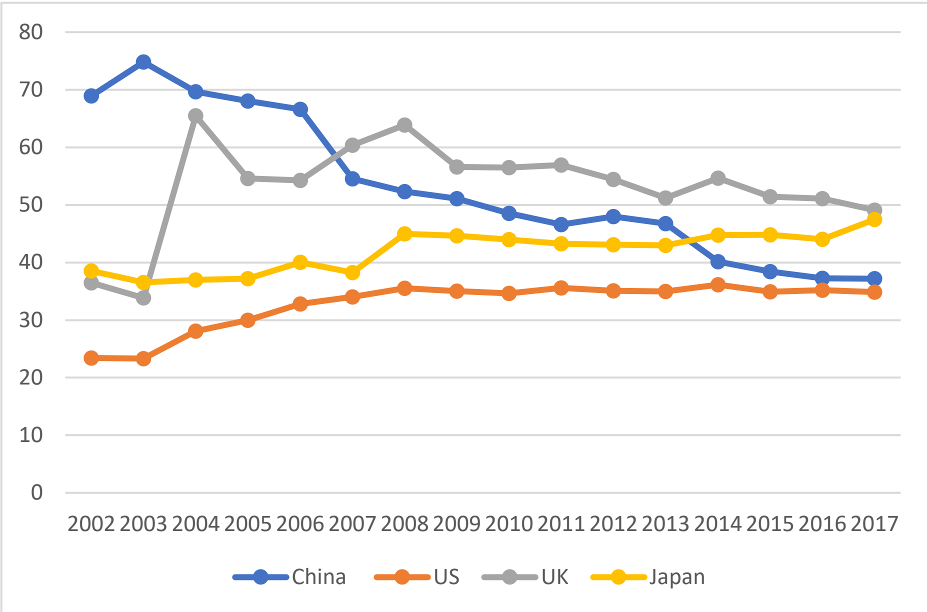
2.5 Banking Features and Performance

As discussed in section 2.3, in order to handle Chinese banks' political and institutional issues, China has enforced a set of gradual but far-reaching reforms. These reforms have had significant impacts. Of particular note is the marked decrease in the degree of bank concentration. As shown in Figure 2.3, in the early 2000s, on average, the banking concentration ratio (proxied by CR5[35]) of China was around 71%, much higher than that of Japan at 37%, or of the US and the UK at 25% and 45%, respectively. The Chinese banking industry at this stage exhibited a highly concentrated market structure and the barriers to entry the industry were fairly high. Then, thanks to the introduction of city and rural commercial banks and the opening up of the industry to

[35] The CR5 is simply the market share of the 5 largest banks (by assets) in the banking market.

foreign competitors, Chinese banking market competition improved (Yin et al., 2015) and concentration declined considerably. The concentration ratio reduced more than half over 2003-2017, from 74% to 35%. In contrast, during this period, the US and Japanese banking systems witnessed a rise in their levels of concentration (see Figure 2.3).

Figure 2.3: Banking concentration ratio of China, the US, the UK and Japan (%).



The concentration ratio is proxied by the CR5 ratio, measuring the market share of the 5 largest banks (by assets) in the banking market.

Source: S&P Global Market Intelligence Platform and Federal Reserve Economic Data

Throughout the sustained transition[36], China saw a steady growth in its banking sector's total size and value. Figure 2.4 shows that the total assets of Chinese banks increased from CNY37 trillion to CNY252 trillion (almost a seven-fold increase) during the period 2002 to 2017. Meanwhile, China's bank assets to GDP ratio rose by nearly 50%, from 118.97% in 2002 to 174.54% in 2017. In contrast to this remarkable increase in the assets of Chinese banks, after the GFC most crisis-affected European banking systems saw a contraction [37]. In 2017, the Chinese banking industry, with total assets of

[36] As specified in section 2.3.

[37] For instance, the total assets of UK banks shrank from US$19.8 trillion in 2008 to US$14.25 trillion in 2017. Over the same time period, Germany's banking sector decreased by 13% (in terms of assets) (from US$11.11 trillion to US$9.64 trillion) and France's by 12% (from US$9.4 trillion to US$8.3 trillion)

US$39.9 trillion, surpassed that of the eurozone, with US$34 trillion, to become the world's biggest banking system by asset size, a sign of the country's increased influence in world finance (Fang et al., 2019). Since 2015, with the collapse of US banking giants and the retrenchment of large European banks after the GFC, China has been running 4 of the world's 5 largest banks (in terms of assets) (Garrido and Chaudhry, 2019)[38].

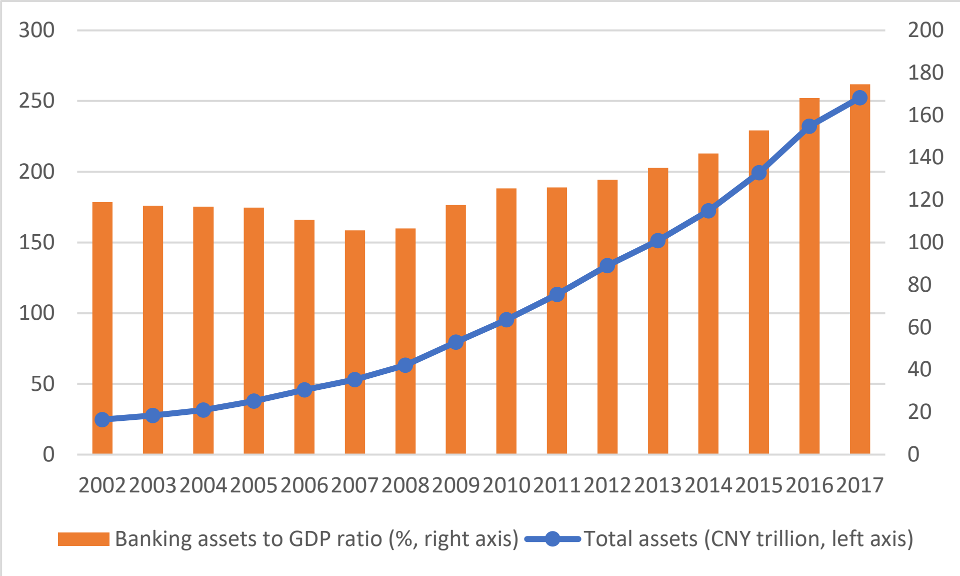
In addition to the asset growth of Chinese banks, Garnaut, Song and Fang (2018) posit that other metrics, such as the numbers of employees or of branches, have presented an overall upward tendency during the past decade. For instance, Chinese banks employed around 2.85 million people in 2008. This figure had increased to 4.7 million in 2017. Whatever metrics are used, the rapid expansion of the Chinese banking system and ongoing financial deepening[39] in China are evident. In these circumstances, some of the benefits and/or costs that may arise from such expansion attracts our attention and these are analysed in Chapter 3.

(Fang et al., 2019).

[38] S&P Global releases yearly the worldwide bank ranking series. To illustrate, in its 2017 listing of the world's 5 largest banks (in terms of assets), the top 4 were Chinese: the Industrial and Commercial Bank of China (ICBC), the Bank of China (BOC), the China Construction Bank (CCB) and the Agricultural Bank of China (ABOC). The ICBC was ranked as the world's largest and CCB, ABOC and BOC came second, third and fourth, respectively (Garrido and Chaudhry, 2019).

[39] Financial deepening generally means the growth of a country's financial system relative to GDP.

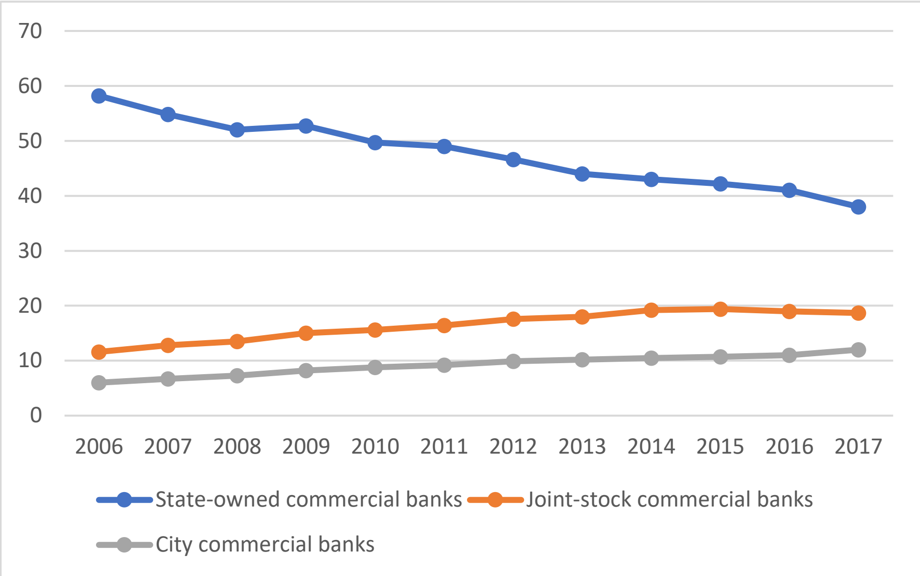
Figure 2.4: Chinese banking sector: asset growth.



Source: S&P Global Market Intelligence Platform and CEIC Data

With the continuous and rapid growth of the asset scale of the entire Chinese banking sector, this sector's asset composition has also changed. Below Figure 2.5 presents the evolution of the market share of different types of Chinese banks in the total banking assets over time. As discussed in above section 2.4, after 20 years of banking reforms, the market share of state-owned commercial banks in the total banking assets has fallen remarkably from around 90% in 1995 to 41% in 2016, because of the strong competition and more aggressive growth strategy of the smaller banks. Figure 2.5 shows that such a downward tendency seems to continue in the future, albeit state-owned banks will remain systemically important owing to their vital roles in China's economy and their huge size. While oppositely, both Chinese joint-stock commercial banks' and city commercial banks' market share in the total banking assets exhibited a steady increasing trend. Specifically, the market share of joint-stock banks increased from below 12% in 2006 to 19% in 2016, and city commercial banks' market share almost doubled between 2006 and 2016 from around 6% to 11% during this period. However, Wu, Song and Chai (2018) suggest that these two types of banks' asset scale growth decelerated in 2017, partially as a result of the shadow-banking tightening and financial deleveraging.

Figure 2.5: Comparison of market share in the total banking assets by bank types (%).



CBRC has no disclosure on rural commercial banks and foreign commercial banks.

Source: CBRC and Wu, Song and Chai (2018)

Another significant impact worth noting is that the reforms have greatly eased the NPL burdens of Chinese banks. Indeed, there were heavy issues of bad debt amongst Chinese banks in the 1990s, given that the industry's average NPL ratio was normally as high as 18% to 29% during this period (China Statistical Yearbook, 2005). In the 1990s, much of the lending by Chinese banks went to state-owned enterprises (SOEs); many of these were operating at a loss and so relied on bank loans to continue financing their operations, and ultimately failed to repay their loans (Fu and Heffernan, 2009). This was particularly the case for the Big Four, which represented over 90% of total banking assets throughout the 1990s (Turner, Tan and Sadeghian, 2012). As state banks, the Big Four conducted a huge amount of policy-directed lending to SOEs during the late 1980s and 1990s (García-Herrero, Gavilá and Santabárbara, 2006). Essentially, they were forced to assume the function of a finance department and to provide financial support to SOEs at this time[40]. Adding to banks' NPLs in the early 1990s, bank lending contributed to a boom and subsequent bust in the Chinese real estate

[40] Lardy (1999) and Ma and Fung (2002) also make this point.

market (Berger, Hasan and Zhou, 2009).

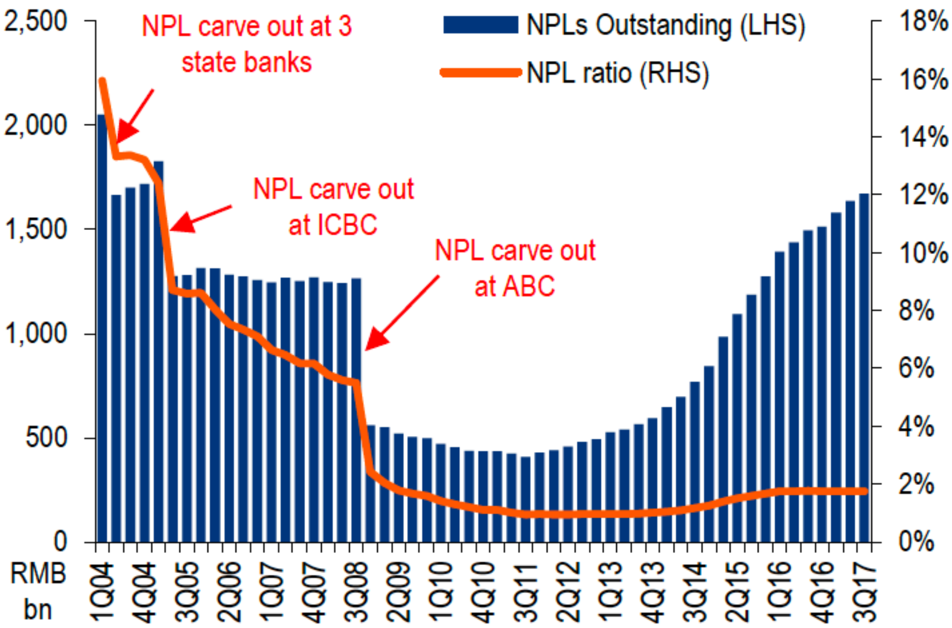
Most of the NPLs were on the balance sheets of the Big Four (that is, ICBC, BOC, CCB and ABOC) (Turner, Tan and Sadeghian, 2012). Then the issuance of the Commercial Banking Law in 1995 was cited as a milestone indicating that the Chinese government sought to alleviate the NPL burdens through institutional reforms. In three stages of banking reform, the Chinese central government proposed a sequence of initiatives to ease the legacy of NPLs and strengthen the capital position of these largest banks. In specific, those initiatives mainly included[41]: (1) NPL carve-out: Four state-owned asset management companies (AMCs) were founded in 1999 to acquire the NPLs of the Big Four. Three rounds of NPL carve-out occurred across the period of 1999 to 2008 to clean up the banks' balance sheets. That is, in the first round, the Big Four transferred NPLs predating 1996 (a total amount of US$170 billion) to the four AMCs during 1999-2000. In the second round, auctions were utilised to transfer non-performing assets. In total, the equivalent of US$15.6 billion and US$18.1 billion in NPLs was auctioned from CCB and BOC to the four AMCs across 2001-2004. The third round proceeded with the approval of an NPL disposal of US$85.5 billion from ICBC to one of the AMCs (Huarong). (2) Capital injection: BOC and CCB each accepted US$22.5 billion of cash contribution to equity base from China's foreign exchange reserve in 2003. In 2005, ICBC got US$15 billion of capital injection, whereas ABOC received CNY130 billion of capital injection in 2008. (3) Foreign strategic investment: HSBC purchased a 19.9% stake of BOCOM in 2004. Temasek and Bank of America invested in CCB in 2005, and Goldman Sachs and RBS became the strategic investors of ICBC and BOC, respectively, in 2006. Most of these raised capitals were utilised to provision or write-off NPLs in the Big Four (Wu, Song and Chai, 2018).

With these efforts, the quality of Chinese banks' loan portfolios enhanced markedly. Figure 2.6 shows that banks' NPL ratio declined by more than 90% (from 16% to 1%) over 2004 to 2011, although the situation worsened again thereafter. While the NPL

[41] According to discussions concerning NPL disposal in García-Herrero, Gavilá and Santabárbara (2006) and Wu, Song and Chai (2018), our study summarises the major initiatives that Big Four have undergone to resolve their NPL burdens in this section.

ratio had doubled by 2017 reaching 2%, the total size of NPLs rose by a factor of 3, from below CN500 billion in 2011 to over CN1,500 billion in 2017. Since the GFC, China has encountered overcapacity problems because of sluggish domestic demand and investment, despite a stimulus package of CNY4 trillion from the government to boost the capacity of domestic enterprises. During the economic downturn, borrowers' debt-servicing ability weakened and the NPL balance started to build up on banks' balance sheets. Chang et al. (2014) suggest that excessive risk-taking in the shadow banking market also contributed to the deterioration in banks' asset quality.

Figure 2.6: Chinese banking sector: asset quality.



NPL ratio: non-performing loan ratio, measured as the sum of non-performing loans divided by the total sum of outstanding loans the bank holds.
ICBC: Industrial and Commercial Bank of China, ABC: Agricultural Bank of China.

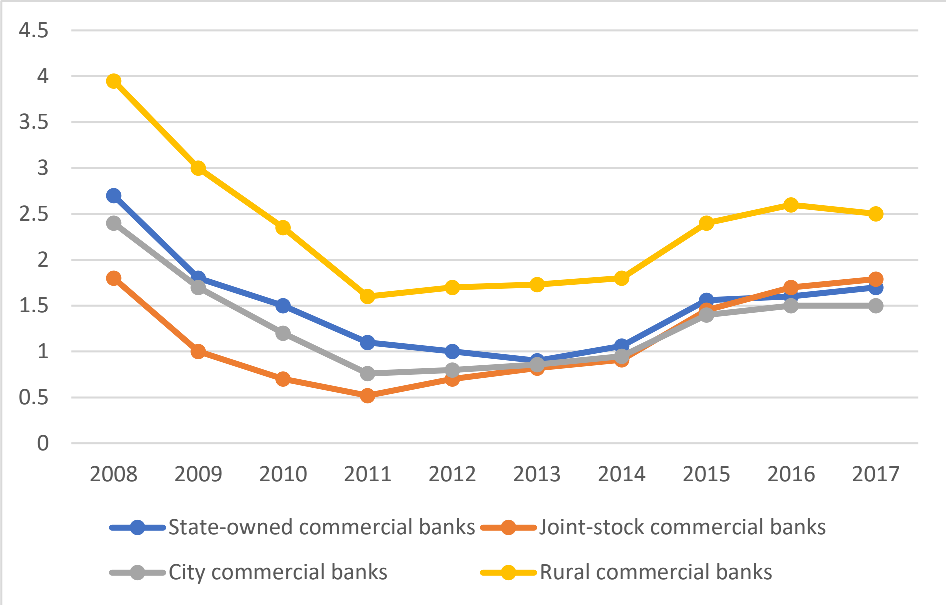
Source: Wu, Song and Chai (2018)

Figure 2.7 compares the asset quality of Chinese banks with different ownership types. As shown, the quality of loan portfolios of all types of Chinese banks improved markedly at the beginning, thanks to the series of government initiatives (as discussed above) to mitigate the legacy of NPLs. Then the asset deterioration has set in for all banks since 2011. Among the four banking types, Chinese rural commercial banks remain among the worst player in the banking market. By the end of 2016, these banks' NPL ratio reached around 2.6%, much higher than that of joint-stock commercial banks at 1.7%, or of state-owned and city commercial banks at 1.6% and 1.5%, respectively. On the one hand, rural commercial banks are specialised in lending to small businesses and farmers in rural regions. Compared with other types of banks, they are likely to face higher probabilities of default risk given their customers are more vulnerable during economic downturns (Boateng, Huang and Kufuor, 2015). On the other hand, these banks' relatively small scale of profits and assets typically leads to less investments in credit risk management and thus gives rise to poorer asset quality of rural commercial banks relative to other types of banks (Berger, Hasan and Zhou, 2009).

Other than rural commercial banks, Chinese state-owned commercial banks are the worst performer compared to city and joint-stock commercial banks, see Figure 2.7. Indeed, recently, all these major bank players have suffered pressure from their NPLs balances. CBRC (2017) examines the asset quality of Chinese state-owned commercial banks over the period of 2012 to 2017 and the results show that all 6 state-owned banks recorded a significant rise in their NPLs accounts, with the largest increase identified for the Industrial and Commercial Bank of China. In total, the 6 banks' NPLs stock amounted to CNY497.2 billion in 2017. However, it should be noticed that the value of NPL ratio of joint-stock banks has recently displayed a tendency of exceeding the level of NPL ratio of state-owned banks.

In the face of this deterioration in their asset quality, Chinese banks employed several tactics to remove troubled assets from their balance sheets. These tactics included the construction of new internal regulations that emphasised the collection of overdue loans, as well as the writing-off and disposal of troubled assets to the four state-owned AMCs (Dong et al., 2016). In relation to the latter, the Big Four in November 2013 packaged their NPLs and sold them through the property rights trading platform, financial asset exchange and AMCs (see Wan, 2018).

Figure 2.7: Comparison of NPL ratio by bank types (%).



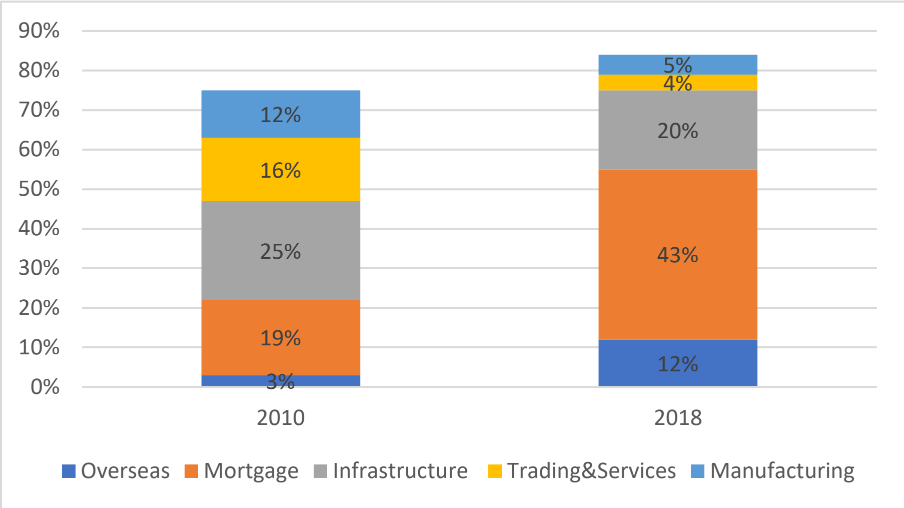
NPL ratio: non-performing loan ratio, measured as the total amount of non-performing loans divided by the total amount of out-standing loans. CBRC has no disclosure on foreign commercial banks.

Source: CBRC and Wu, Song and Chai (2018)

An interesting point worth noting is that the distribution of Chinese banks' new loans across sectors has changed over recent years (see Figure 2.8). Compared with 2010, when banks' lending was distributed relatively evenly across the main sectors, by 2018 it displayed a much more concentrated pattern, with a focus on the mortgage (43%), infrastructure (20%) and overseas sectors (12%). Thus, rather than manufacturing enterprises, our study suggests that the next round of build-up of NPLs will more likely be led by mortgage loans, bank infrastructure lending (especially to local government funding vehicles) and overseas loans (e.g., the Belt and Road initiative[42]).

[42] "First proposed by President Xi Jinping in 2013, the Belt and Road initiative would develop and construct a vast network of railroads and shipping lanes between China and 65 countries in Asia, North Africa, the Middle East and Europe and cost up to US$1.2-1.3 trillion by 2027" (Morgan Stanley, 2018).

Figure 2.8: Net new loan allocation by major sectors in 2010 and 2018.



Source: S&P Global Market Intelligence Platform

Financial liberalisation is typically deemed as one of the important elements of China's banking sector reform (Dong, Girardone and Kuo, 2017). According to García-Herrero, Gavilá and Santabárbara (2006) and Dong, Girardone and Kuo (2017), during the past four decades, liberalisation efforts have gone in the following three directions. First, market-oriented practices are introduced and promoted in the operating of the Chinese banking industry. For instance, the credit quotas on Big Four were removed and government intervention in commercial lending was forbidden in 1999. From the end of 1999, private capital was permitted to enter joint-stock commercial banks and city commercial banks. Besides, the remuneration of excess reserves was cut by the PBOC four times[43] over 1998-2005, in order to encourage banks to invest their assets instead of hoarding liquid assets. Second, interest rates are liberalised by the PBOC. The process of interest rate liberalisation is gradual and not yet completed. It contains the market-based reform of lending and deposit rates, as well as liberalisation of inter-bank lending rates and bond market interest rates; see below Table 2.3 for a list of major initiatives completed during this process. Overall, this liberalisation allows banks to price their deposits and loans independently and improves the role of market forces in

[43] Reserve requirements lowered from 20% to 8% in 1998, and again to 6% in 1999. A further reduction on reserve requirements from 1.62% to 0.99% was observed over 2002-2005 (García-Herrero, Gavilá and Santabárbara, 2006).

resource allocation. Third, the Chinese banking market has gradually opened up to foreign competitors since 2001. To illustrate, foreign banks were only permitted to provide foreign currency services in 2001. Then they were allowed to provide local currency services – including deposit-taking, loans, and other services – to foreign corporate clients and individuals from 2002, to Chinese enterprises from 2003, and to Chinese individual customers from 2006[44] (WTO WT/L/432, 2001).

The financial liberalisation discussed above is usually believed to remarkably enhance bank governance, efficiency and competition in China, thereby improving the earning ability of Chinese banks (Berger, Hasan and Zhou, 2009; Liu, 2017). Indeed, benefiting from China's sustained rapid economic growth[45] and the phased removal of NPLs of the Big Four and the financial liberalisation discussed above, the profitability of Chinese banks greatly increased in the first decade of the century (see Figure 2.9). The industry average of banks' return on equity (ROE) ratio increased from only 4% in 2002 to 15% in 2005, 18% in 2007 and more than 20% in 2010. Another profitability proxy, the return on assets (ROA) ratio, almost doubled over the period 2002 (0.65%) to 2010 (1.14%). Nevertheless, with further deregulation, the profit margins of Chinese banks have been under pressure in recent years. As shown in Figure 2.9, both ROE and ROA decreased after 2013.

[44] Later, from 2006, the Chinese government has been proposed a series of initiatives to further relax the operating environment for foreign banks. For instance, making efforts to enhance autonomy in business development for foreign banks, one of the latest policy amendments on foreign banking institutions is that foreign banks can engage in custodian and consultancy services without prior Chinese government approval from 2017 (CBRC, 2017a).

[45] Throughout the 2000s, China's GDP has maintained an average annual growth rate of around 10% each year (World Bank Open Data).

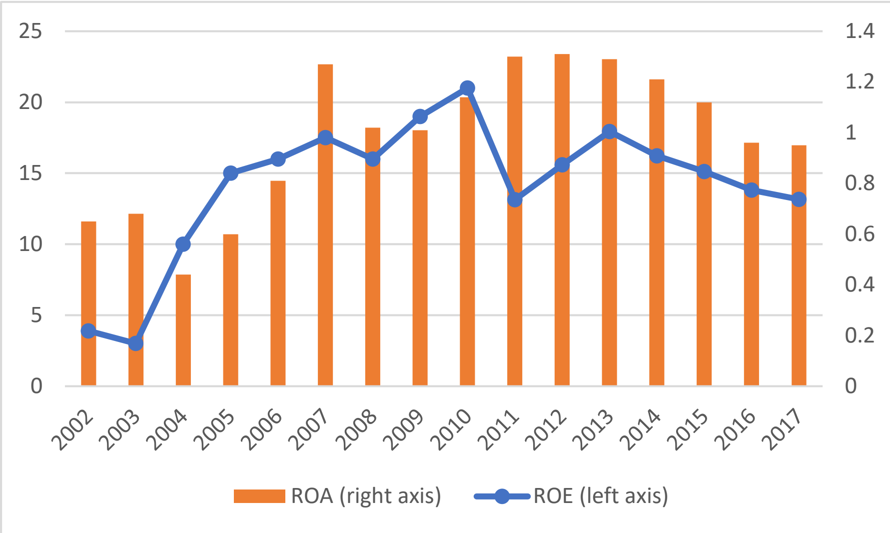
Table 2.3: Interest rate liberalisation process.

Market-based reform of lending and deposit rates
Loans
1987 Surcharge until 20% on reference rates on loans (working capital)
1996 The band changes to +-10% around reference rates
1998 Increase of upper limit to 20% (RCCs 50%)
1999 Increase of upper limit to 30% (RCCs and large enterprises 10%)
2003 Increase of upper limit to pilot RCCs to 100%
2004 Increase of upper limit to 70% and to RCCs to 100%, lower limit remains at 90%
2004 Liberalisation of upper limit of RMB lending rates (excluding RCCs, that increase until 130% above reference rates)
Deposits
1999 Negotiation on rates on over CNY30 million deposits with maturity above 5 years for insurance companies
2002 Same scheme for Social Security Fund
2003 Same scheme for China Postal Saving and Remittance Bureau
2004 All kind deposit rates can adjust downward
Liberalisation of inter-bank lending rates
1990 Pilot liberalisation of inter-bank lending market and rates
1996 Creation of unified inter-bank market
1996 Abolish the upper limit of interbank lending rates
Liberalisation of bond market interest rates
1996 Market based issuance of government bonds on pilot markets (stock markets)
1997 Utilization of the inter-bank market to deal in inter-bank bond repo transactions. Liberalisation of the bond repo interest rates
1998 Market-based issuance of financial bonds by the policy banks
1999 Market-based issuance of government bonds

RCCs: rural credit cooperatives.

Source: PBOC (2005) and García-Herrero, Gavilá and Santabárbara (2006)

Figure 2.9: Chinese banking sector: profitability (%).



ROA (right axis): return on assets ratio, estimated as net income divided by total assets; ROE (left axis): return on shareholders' equity ratio, estimated as net Income divided by shareholders' equity.

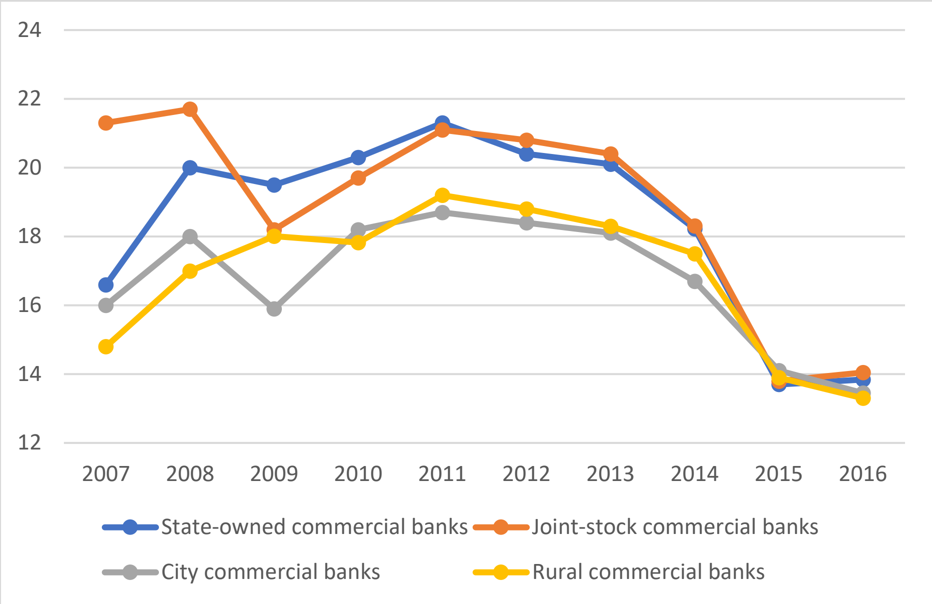
Source: S&P Global Market Intelligence Platform and Federal Reserve Economic Data

Hou et al. (2018) propose that several factors may account for the more recent reduction in bank profitability in China. These include: (i) the increase in internet finance disrupting banks' core interest-rate bearing business; (ii) banks' non-interest income being reduced by both Fintech and policy headwinds; (iii) the rise in banks' NPLs; and (iv) deregulation of interest rates significantly lowering banks' net interest margin. An earlier study by Xu, van Rixtel and van Leuvensteijn (2016) suggested that the traditional interest income on average represents roughly 70% of Chinese banks' total earnings. As such, the profitability of Chinese banks is mostly driven by the credit and interest rate cycles. Accordingly, it is no surprise to see recent unfavourable bank margins, since the Chinese economy has seen low interest rates and low inflation. In this thesis, we examine empirically the factors underlying the profitability of Chinese banks in Chapter 4.

Figure 2.10 compares the earnings of different types of Chinese banks. It shows that there has been a significant drop in the return on equity ratio for all bank types, matching the recent weak profitability performance of the Chinese banking sector. The state-owned banks and joint-stock banks are profit leaders compared with city and rural commercial banks. Indeed, the former group of banks are large Chinese banks with diversified products and services, as well as extensive branch networks, and they have natural advantages in carrying a more diversified income mix (Shih, Zhang and Liu, 2007). In contrast, the income mix of the latter group of banks is likely to be concentrated and more volatile in line with the interest rate and economic cycle (García-Herrero, Gavilá and Santabárbara, 2009). On average, there is a substantial difference in the return on equity ratio between the two groups. However, since 2013, this dispersion has been reducing, alongside the overall decrease in all banks' profits. Moreover, the continuously poor performance of the rural commercial banks could be partially explained by the fact that the growth in provisions because of banks' high NPL ratio (see Figure 2.7) has been considerably dampening their earning ability.

Actually, the period before the GFC was a 'golden era' for the development of Chinese joint-stock commercial banks as large state-owned commercial banks were busy with internal restructuring at that time (Lin and Zhang, 2009). From 2001 to 2006, the WTO accession led many joint-stock banks to go public. To illustrate, after the accession of China to the WTO in 2001, major joint-stock banks, such as the China Minsheng Bank, Huaxia Bank and Shanghai Pudong Development Bank, got listed on the A-share market. The IPOs notably improved their brand recognition and banks' access to capital markets (Wu, Song and Chai, 2018). This led to a remarkable expansion in their size and business operations. As a result, Chinese joint-stock commercial banks achieved a return on equity ratio of 19%-21% from 2001 to 2007, much higher than that of rural commercial banks, at 12%-15%, or of city and state-owned commercial banks at 14%-16% and 17%-20%, respectively (data reported by CBRC and Federal Reserve Economic Data). As displayed in Figure 2.10, the profit growth of joint-stock banks has slowed significantly after the GFC.

Figure 2.10: Comparison of ROE ratio by bank types (%).



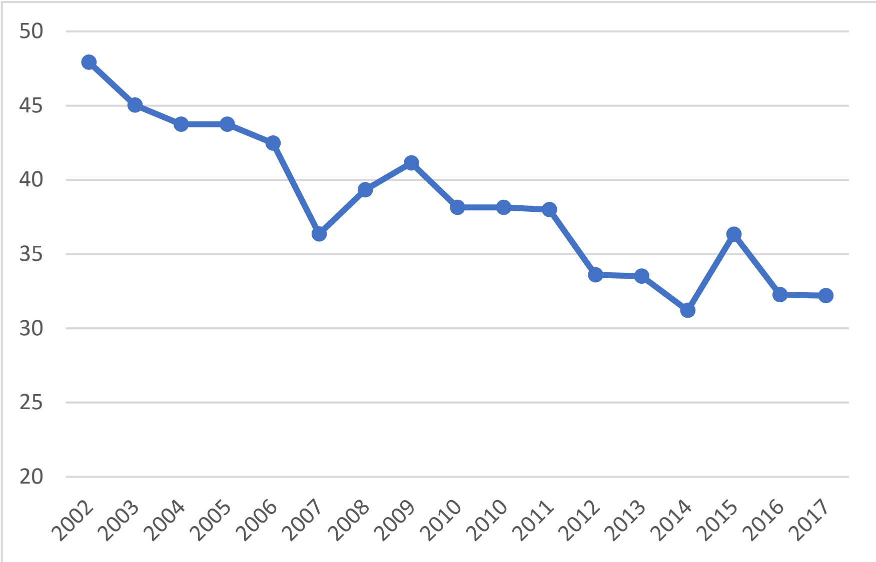
ROE ratio: return on shareholders' equity ratio, measured as net income divided by shareholders' equity. CBRC has no disclosure on foreign commercial banks.

Source: CBRC and Wu, Song and Chai (2018)

Overall, returns from the banking sector seem now to be flagging. When interest rate cuts[46] and liberalisation squeezed Chinese banks' earning ability, their cost efficiency was also affected. The liberalisation of the financial sector ramped up internet financing and thus massive amounts of funds entered the capital market, with a resurgent A shares market (KPMG, 2017). Chinese banks are encountering fierce competition from the Fintech players and therefore the major banks have followed one another in increasing their rates on interest-bearing deposits (though this leads to an increase in costs) in order to retain their shares (Tan, Floros and Anchor, 2017). As a whole, the Chinese banking sector has managed to enhance, slowly but stably, its cost efficiency over the last two decades, despite a renewed focus on cost containment in the post-crisis period (see Figure 2.11). Overall, the cost-to-income ratio fell by 33%, from 48% in 2002 to 32% in 2017.

[46] For instance, the interest rate was cut by the PBOC five times in 2014, to 4.706%, and further lowered six times in 2015, to 4.35% by the end of the third quarter.

Figure 2.11: Chinese banking sector: cost-to-income ratio (%).



Cost-to-income ratio is calculated by dividing the operating expenses by the operating income generated.

Source: S&P Global Market Intelligence Platform and Federal Reserve Economic Data

2.6 Banking Capital Management

In addition to the NPLs problem discussed above, we now turn to discuss another long-standing obstacle that has hindered the Chinese banks: the undercapitalisation of the Chinese banking system. Indeed, over the 1990s and early 2000s, Chinese banks were plagued by severe capital shortages. The capital to assets ratio of Chinese banks was 4.91% in 1993, 3.78% in 1995, 2.77% in 1997, 4.78% in 1999, 4.21% in 2001 and 3.09% in 2003 (PBOC, 1998 and García-Herrero, Gavilá and Santabárbara, 2009). At this time, the Chinese banking was seriously undercapitalised relative to minimum international regulatory standards. China made huge efforts to improve the capitalisation of its banking system. The government proposed a set of initiatives, including direct capital injection, acquiring fresh capital from foreign investors and raising new capital through listing banks on stock exchanges (McGuinness and Keasey, 2010; Dong et al., 2016).

Specifically, during the period of the first phase, the second phase and early stage of the third phase of Chinese banking reform, the National People's Congress has worked hard to mitigate the deterioration in the balance sheets of the Big Four. For example, in March 1998, it passed a plan submitted by the State Council to issue special government bonds to provide capital injection into these banks. The total value of this capital injection plan amounted to CNY270 billion (US$32.5 billion, equivalent to nearly 3% of China's GDP or 55% of central government revenues in that year). Later, in December 2003, the Central Huijin Investment Company was established, based on the investment of foreign exchange reserves by the State Administration of Foreign Exchange. Central Huijin injected a total of CNY499.6 billion (US$60.4 billion) into the Big Four: US$45 billion into the BOC and CCB in December 2003, CNY3 billion into the BOCOM in June 2004, and US$15 billion into the ICBC in April 2005, in the second phase of the plan. All funding sources were generated from the country's official foreign exchange reserves and borrowing from the Ministry of Finance.

Meanwhile, Chinese government has permitted foreign strategic investors entering domestic banks' capital for the purpose of diversifying ownership and strengthening management quality. To illustrate, Bank of America acquired 9% of CCB (amounting to US$2.5 billion) in 2005, whereas Temasek, a state-owned financial holding company from Singapore, also invested in CCB with US$1 billion in the same year. In 2006, Goldman Sachs and RBS invested in ICBC and BOC, respectively. Across the period of 2004 to 2008, a total of 24 domestic banks raised new capital from 36 foreign investors (García-Herrero, Gavilá and Santabárbara, 2009).

The IPO decisions made by the state-owned banks during the WTO post-accession period were widely considered to be a big step forward for Chinese banks to strengthen their capital positions (Ariff and Can, 2008). As Table 2.4 shows, the listing status of the ICBC increased its capital account by CNY97.1 billion, leading to an overall 44.3% capital increase in 2006 compared with the pre-IPO capital balance of CNY326.2 billion. Capital reserve increases for the BOC and CCB were CNY71.1 and CNY42.1 billion, and there was an 80.9% increase in the capital performance of the Bank of Communications.

Table 2.4: Total capital increases from banks' public listing (CNY billion).

Bank	Total capital (at the end of previous term) [a]	Proceeds from IPO including issuance cost [b]	Share capital increase [c]	Capital reserve increase [d]	Percentage of total capital increase by IPO [e=(c+d)/a]
ICBC	326.2 (June 2006)	126.6			
		46.6			
Total		173.3	47.5	97.1	44.3
BOC	233.8 (Dec. 2005)	90.0			
		20.0			
Total		110.0	35.9	71.1	45.8
CCB	200.9 (June 2005)	74.6	30.5	42.1	36.1
BOCOM	52.1 (Dec. 2004)	18.0			
		25.2			
Total		43.2	9.9	32.3	80.9

ICBC: Industrial and Commercial Bank of China, BOC: Bank of China, CCB: China Construction Bank, BOCOM: Bank of Communications.

Source: Ariff and Can (2008)

The recapitalisation programmes discussed above reflect China's efforts to restructure state-owned commercial banks and are crucial elements in its banking reform process (Dong et al., 2016). All these programmes have significantly boosted capital positions of Chinese banks, thereby enhancing the stability of the banking industry. Indeed, the capital to assets ratio of the Chinese banking system increased substantially from 3.09% in 2003 to 6% in 2008, again to 8.44% in 2015[47]. The capitalisation of Chinese banks was further strengthened after China's accession to the Basel Committee on Banking Supervision in 2009[48]. Since then, China has been able to discuss conditions of the global financial market and monetary policy with other central authorities, as well as to facilitate cooperation with these organisations in the banking regulatory area.

[47] Data reported by S&P Global Market Intelligence Platform and PBOC.

[48] At its 10th-11th March 2009 meeting, the Basel Committee announced the expansion of its membership and it invited representatives from following countries to join it: Australia, Brazil, China, India, Korea, Mexico and Russia (Knaack, 2017).

Besides, China has made commitments to fully adhere to the Basel II capital framework, and later Basel III capital rules[49] (CBRC, 2011a). Following Basel III guidance, the CBRC and PBOC undertook a programme of promoting a well-capitalised and stable banking sector in China.

For instance, following the Basel III capital criteria, the CBRC issued a series of capital rules in 2011 (see Table 2.5) to update the previous relaxed domestic regulations in order to boost the quality and quantity of the core capital of Chinese banks[50]. Specifically, Basel III required a minimum of 4.5% in core Tier 1 capital ratio, an increase from the earlier 2% level in Basel II (BIS, 2011). However, Table 2.5 displays that the CBRC amended this requirement and implemented a 5% rule for core capital across the Chinese commercial banks. In addition, the CBRC enforced a minimum of 6% in Tier 1 capital adequacy ratio and a minimum of 8% in capital adequacy ratio. It should be pointed out that an additional 2.5% of capital conservation buffer is further required by the CBRC over and above the minimum capital requirements, finally equalling 7.5% in core Tier 1 capital ratio, 8.5% in Tier 1 capital adequacy ratio and 10.5% in total capital adequacy ratio (CBRC, 2011a).

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[49] It should be noted that Chinese banks were never regulated under Basel I regulations; the CBRC moved directly to Basel II and Basel III standards. Under the new Basel III requirements, the initiation of new capital rules for Chinese banks started from 1st January 2013, representing a new landmark regulatory scheme for the Chinese banking system.

[50] Overall, Basel III imposes tighter requirements on bank capital and eligible capital instruments in order to force banks to focus on core capital elements instead of debt-like substitutes (BIS, 2011).

Table 2.5: Regulatory capital requirements on Chinese banks.

	CBRC requirements
Regulatory capital adequacy ratio calculation	A commercial bank shall use the following formula to calculate its capital adequacy ratios: **1. Capital adequacy ratio:** ➢ $\frac{Total\ capital - Regulatory\ deductions}{Risk\ weighted\ assets} * 100\%$ **2. Tier 1 capital adequacy ratio:** ➢ $\frac{Tier\ 1\ capital - Regulatory\ deductions}{Risk\ weighted\ assets} * 100\%$ **3. Common equity Tier 1 capital adequacy ratio:** ➢ $\frac{Common\ equity\ T1 - Regulatory\ deductions}{Risk\ weighted\ assets} * 100\%$
Regulatory requirements on capital adequacy	The total regulatory capital of a commercial bank consists of the sum of common equity Tier 1 capital, additional Tier 1 capital and Tier 2 capital. A commercial bank shall be subject to the following minimum capital requirements at all times: 1. Common equity Tier 1 capital adequacy ratio no less than 5%; 2. Tier 1 capital adequacy ratio no less than 6%; 3. Capital adequacy ratio no less than 8%. A commercial bank shall be subject to the capital conservation buffer over and above the minimum capital requirements. The conservation buffer shall be 2.5% of total risk weighted assets of the bank and comprised of common equity tier 1 capital. A systemically important bank shall be subject to a capital surcharge in addition to the minimum capital requirements.

Where the Table offers a summary of current regulatory capital requirements that specified by the CBRC (in line with Basel III standards) on Chinese banks.

Source: CBRC (2011a)

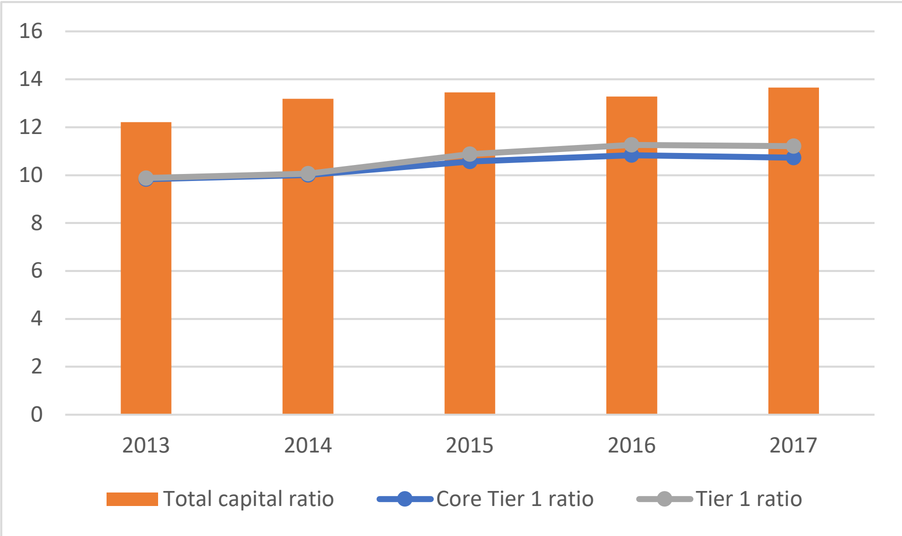
Moreover, given that the world banking system's increasing complexity has tended to put financial stability at risk, the Basel Committee introduced a new countercyclical buffer in 2010, and an additional capital buffer was added in 2013 for identified global systemically important banks (BIS, 2013a). See specific explanations concerning the list of global systemically important banks and their corresponding capital surcharge in section 3.3.2. Correspondingly, Chinese systemically important banks (i.e., the Big Four as identified by BIS based on the five-indicator appraisal framework)[51] were subject to an additional capital surcharge (1% or 1.5%) in addition to above minimum capital requirements in order to limit the negative externalities associated with the potential failure of these "too big to fail" banking institutions (see Table 3.2).

Overall, in accordance with rigorous international standards, the CBRC implemented a tighter regulatory framework that addresses qualified capital and higher minimum capital requirements in the Chinese banking system[52]. Therefore, the banks witnessed notable improvements in their resilience to adverse shocks in recent years through a substantial strengthening of their capital positions (see Figure 2.12), albeit the entire sector remains undercapitalised compared with debt financing. Evidently, as exhibited in Figure 2.12, Chinese banks' various capital indicators all meet the CBRC's minimum capital requirements. For example, the Tier 1 ratio was 9.88% in 2013, 10.88% in 2015, and 11.21% in 2017; all the values were higher than the minimum requirement of 8.5% (much higher than the Basel III criterion of 6%).

[51] In this respect, section 3.3.2 details BIS's process of identification of global systemically important banks based on the five-indicator appraisal framework.

[52] Following Basel III guidance, liquidity caps (i.e., a minimum requirement of 100% in liquidity coverage ratio and net stable funding ratio) were also introduced to Chinese banks to address the increasing concern about over-leveraging and the build-up of systemic risks in the banking market (BIS,2013b and BIS, 2014).

Figure 2.12: Chinese banking sector: capital performance (%).



Source: S&P Global Market Intelligence Platform

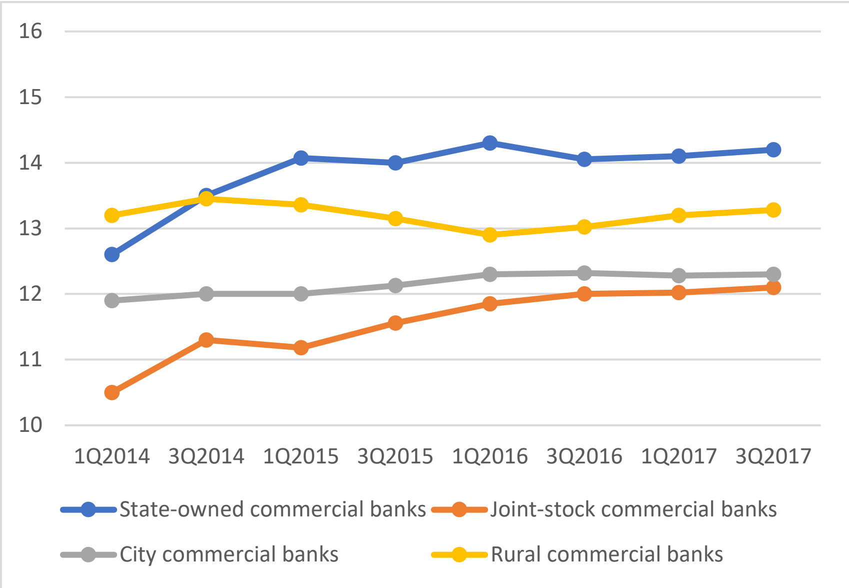
Figure 2.13 presents the level of capital adequacy ratio of Chinese banks with different ownership structures. The largest state-owned commercial banks, have the highest capital position among all types of banks and satisfy the CBRC minimum requirement of 10.5% (much higher than the Basel III criterion of 8%). Indeed, as discussed above, the listing status of the BOC, BOCOM, CCB and ICBC has remarkably enhanced the capital account of Chinese state-owned commercial banks. Similarly, Chinese joint-stock, city and rural commercial banks all meet the Basel III requirement of 8% with joint-stock banks being the riskiest financial segment. On average, all types of banks are found to be more resilient to adverse economic shocks. For instance, a 12.7% capital increase was observed for state-owned commercial banks from 2014 to 2017. Meanwhile, the capital adequacy ratio of joint-stock banks enhanced from 10.6% to 12%.

Nevertheless, Wu and Shen (2019) point out that both joint-stock and city commercial banks have been facing increasing capital pressure recently – need more fresh capital to maintain their financial stability, given that there has been increasing risk-taking of these banks on both sides of their balance sheets. More specifically, lately, on the asset side, these banks have begun to heavily engage in investment assets, mainly more risky non-standardised credit assets that are considered capital-intensive, such as wealth management products, beneficiary rights and trust products. Indeed, the share of investment assets accounted for around 30%-40% of total assets for joint-stock and city commercial banks, as of December 2017[53]. Besides, on the liability side, a widespread shift away from stable core deposit funding towards volatile short-term wholesale funding has been reported for Chinese joint-stock and city commercial banks. This can be reflected by the fact that the total share of borrowing from the interbank market and non-financial institutions increased sharply from 12% in 2006 to 31% in 2017 and from 8% in 2006 to 23% in 2017 for joint-stock banks and city commercial banks, respectively. Meanwhile, this ratio rose from 7% to 13% for state-owned banks and rural commercial banks witnessed an increase from 8% to 15%[54]. Consequently, the risks are not evenly distributed in the banking industry – joint-stock banks and city commercial are the most leveraged banking segments. This leverage could be a significant source of systemic risk and exposes them to credit and liquidity risk (Elliott, Kroeber and Qiao, 2015; Bengtsson, 2016). All of these suggest that joint-stock and city commercial banks are more likely to face capital shortage in the case of unexpected adverse shocks compared with other types of banks. More capital buffers are needed to set aside for these banks in order to strengthen their ability to cope with adverse shocks in the financial system (or the economy).

[53] Data reported by S&P Global Market Intelligence Platform.

[54] Data reported by CBRC and S&P Global Market Intelligence Platform.

Figure 2.13: Comparison of CAR ratio by bank types (%).



CAR ratio: capital adequacy ratio, calculated by dividing a bank's capital by its risk-weighted assets. CBRC has no disclosure on rural commercial banks and foreign commercial banks.

Source: CBRC and Wu, Song and Chai (2018)

Other than endeavouring to boost bank capital reserves, the CBRC also required banks to adopt new accounting disclosure standards (IFRS 9[55]) from 2017. This was to address problems such as financial instruments being classified arbitrarily, and provisions for impairment of financial assets not being made adequately or in a timely manner (which may lead to an insufficient minimum capital holding by banks) (Bholat et al., 2018). The IFRS 9 accounting standards introduced more prudential and transparent accounting disclosure schemes – the classification, measurement and recording of impairment of financial instruments are the most affected areas for Chinese banks (KPMG, 2017).

In fact, IFRS 9 imposes pressure on Chinese banks' capital reserves – challenges emerge with changes in the recognition of the impairment of financial instruments. That is, the adoption of IFRS 9 actually has prompted an urgent need for Chinese banks,

[55] After the GFC, G20 (the Group of Twenty nations) asked the International Accounting Standards Board to step up its revision of accounting standards concerning financial instruments. Accordingly, IFRS 9, issued by the International Accounting Standards Board in July 2014, was implemented by Chinese banks (requested by the Ministry of Finance) from 31st March 2017.

particularly medium-sized and small banks, to raise more capital. Originally, Chinese banks classified 'special mention loans' as those which were fewer than 90 days overdue rather than recording them as impaired loans on bank books, whereas IFRS 9 recognised them as impaired loans (CBRC, 2011b and Wang and Liu, 2012). Since 2017, IFRS 9 disclosure standards for recognising such types of impaired loans in Chinese banks could obliterate regulatory capital at smaller banks as they typically set aside lesser sums for provisions and capital for such troubled loans, and thereby asset quality within the banking sector deteriorates (KPMG, 2017). Indeed, Zhang, Yin and Zhang (2018) point out that the merger of special mention loans with the impaired loan account could wipe out banks' capital holdings significantly and that many banks might not meet minimum regulatory requirements. This is especially a challenge for medium-sized and small Chinese banks, where the recognition of bad debts is traditionally weak. In the worst scenario, some small banks may face regulatory capital wipe-out due to the surge in their non-performing loans.

2.7 Recent Changes in Business Models and Strategies

The banking reforms, the experience of the GFC and the post-crisis market environment have had substantial effects on the Chinese banking system. In response to their new operating landscape, Chinese banks have been adjusting their business models and strategies. One such underlying change is the shifting of bank assets to shadow banking activities (see Lin, Sun and Wu, 2015; BIS, 2018; and Hou et al., 2018). Indeed, the aggregated shadow banking credits (considering only the banks' shadow banking activities) accounted for only 3.34% of total banking assets in 2005. This ratio rose sharply to 7.55% in 2009, 23.12% in 2013 and 27.5% in 2017[56]. As of December 2017, total sector exposures amounted to CNY69 trillion (increased from CNY1.27 trillion in 2005), equivalent to nearly 70% of China's total GDP in that year[57] (Elliott, Kroeber and

[56] Author's own calculations, based on data from the PBOC and Financial Stability Board.

[57] This is when only the banks' shadow banking credits are considered. The total exposures of shadow banking credits within the Chinese financial system as a whole had reached CNY119 trillion by the end of 2017, with the total credit to GDP ratio at 151% (Wu and Shen, 2019).

Qiao, 2015; Wu and Shen, 2019).

The term 'shadow banking' was coined by McCulley (2007), although the literature on shadow banking has not reached a consensus on its definition. According to Hou et al. (2018), widely used definitions of shadow banking can be categorised into two perspectives. "*The first perspective, outlined by the Federal Reserve Bank of New York, defines shadow banking as financial institutions, markets and instruments that can reproduce the core business of commercial banks. The second perspective views shadow banking as a system of credit intermediation that involves activities and institutions outside the regular banking regulation system (Financial Stability Board, 2011)*" (Hou et al., 2018, page 308). Both emphasise the role of non-bank financial intermediaries in replicating the core businesses of traditional banks (i.e., the functions of liquidity, maturity and credit transformation).

In short, in developed countries, shadow banks denote primarily unregulated financial intermediaries outside the banking system that still transfer credit to the system. That is, shadow banking, which originated in the wave of financial liberalisation in the 1980s, refers to the collection of non-bank financial institutions that serve bank-like activities (primarily lending) but outside normal bank regulations in advanced economies (Hou et al., 2018). Typically, these non-bank financial intermediaries have no access to the deposits, have no ability to borrow from public liquidity sources such as central banks, and are not subject to traditional banking regulations. They are normally parallel with commercial banks to transfer credit to the system through many financially innovative activities (e.g., securitisations, mortgages and repurchase agreements) with a relatively higher leverage ratio (Bengtsson, 2016).

However, in contrast to shadow banking in developed economies, shadow banking in China has a different definition. China has a bank-centred shadow banking market; that is, shadow banking operations mainly take place inside the banking sector, with commercial banks playing a major role and only a small portion of shadow banking activities being undertaken by non-bank financial intermediaries (Li and Lin, 2016). In China, shadow banking basically comprises banks' regulatory arbitrage practices (e.g., bankers' acceptances) that circumvent regulatory requirements in order to offer credits to individuals and businesses who are incapable of acquiring funds from traditional commercial banks (PBOC, 2013; Lin, Sun and Wu, 2015).

For instance, certain banks are restricted by regulations (e.g., lending quotas such as the 75% loans to deposits ratio[58]) from extending credits to certain industries that need funding (Financial Stability Board, 2018). Some large banks are reluctant to offer credits to small and medium-sized firms due to the information asymmetry that can stem from these firms' potentially distorted financial reports. Hence, banks innovate new financial instruments to transfer funds in such a way that the regulations on lending can be circumvented. For example, banks can utilise interbank accounts that have fewer lending restrictions or cooperate with unregulated financial intermediaries in offering funds. In simple terms, differing from the aforementioned definition of shadow banking in developed economies, the Chinese style shadow banking describes the practices of banks to offer liquidity to the system without making loans to avoid violating various regulations[59]. In this thesis, we utilise shadow banking activities to represent such regulatory arbitrage practices of sample Chinese banks.

In China, the main objective of shadow banking activities is simply to meet normal credit needs that banks cannot otherwise meet because of various regulatory restrictions (e.g., capital constraints) (PBOC, 2013). These transactions increase the share of direct financing and make financial services cheaper, thus stimulating China's economic growth (Elliott, Kroeber and Qiao, 2015). Moreover, they offer substantial rewards to Chinese banks. For example, shadow banking activities could be practised by banks with recourse to identify the optimal capital level that meet the market's risk perception as opposed to regulatory requirement. That is, by engaging in shadow banking activities, Chinese banks are able to evade regulatory minimum capital requirements, and hence shift regulatory burdens and reduce compliance costs to

[58] The Chinese government removed the 75% cap on the loans to deposits ratio in May 2015.

[59] According to the PBOC (2013), typically, the following types of financial activities would be considered as banks' shadow banking transactions: inter-bank market activities, wealth management products, trust beneficiary rights, guarantees, financial leasing and bankers' acceptances.

maximise their profits (Plantin, 2015). Hou et al. (2018) argue that "*the growth of shadow banking activities stimulates banking competition, facilitates the transfer of fund price information for managers, and promotes the technical innovations of banks, which can also strengthen banks' market incentives and capabilities to minimize costs. Moreover, to commence shadow banking activities, banks usually reshape the internal mechanics of management, resulting in reduced operational inefficiency*" (page 315). Furthermore, by participating in a variety of shadow banking activities, banks can realise efficiency gains through economies of scale and scope (Goddard, McKillop and Wilson, 2008).

Nevertheless, these benefits often come at the cost of reduced financial stability. In practice, compared with conventional banking activities, shadow banking activities are conducted on a much smaller capital base and with a different, and commonly lesser degree of regulatory oversight (Lin, Sun and Wu, 2015). Since various types of shadow banking activities are complicated and opaque, there is too little transparency in the shadow banking market, and this gives rise to an opaque debt structure of banks that are heavily involved in this market. The scale and spread of risks are difficult to detect and easily overlooked (see Financial Stability Board, 2011). Moreover, moral hazard incentives arise when bank managers have the expectation of government bailouts in the event of financial distress. In this respect, the managers of large banks might be inclined to take undue risks by heavy engagement in risk-intensive shadow banking activities that maximise banks' income while passing losses to the government (Gennaioli, Shleifer and Vishny, 2013).

Moreover, shadow banking operations increase the leverage of banks. This leverage could be a significant source of systemic risk and exposes banks to liquidity and credit risk. This argument is supported by Elliott, Kroeber and Qiao (2015) and Bengtsson (2016), while Bengtsson (2016) further suggests that when market participants overlook tail risks, shadow banking sustains excessive insurance and hence excessive leverage, which renders banks and the economy very sensitive to unexpected adverse shocks. Cai et al. (2018) argue that financial interconnectedness increases through the re-intermediation process of shadow banking. During any crisis period, financial interconnectedness will propagate shocks beyond their initial impact, amplifying them in the process, as exemplified by the GFC. All of these features could increase the risk of financial instability, which is the main reason there is a focus on shadow banking activities today.

A substantial portion of Chinese banks' shadow banking activities are funded by short-term wholesale funds (Wu and Shen, 2019)[60]. Over recent years, a growing number of Chinese banks have employed risky wholesale financing to sustain their remarkable assets expansion (see Vera, Onji and Gai, 2014; IMF, 2017a; and Wu, Song and Chai, 2018). The ratio of wholesale funding to total funding of Chinese banks increased from 4% in 2006 to 9% in 2017. This ratio was much higher for the joint-stock banks. By the end of 2017, these banks' proportion of wholesale funding reached an average of 24% (Wu, Song and Chai, 2018). Wholesale funding greatly diversifies the funding resources for banks. However, as Chinese banks become more dependent on wholesale funds, there is an increasing concern among policymakers about repeating the "Lehman episode" (IMF, 2017a; Qi and Yang, 2017). For example, as an article in the *Financial Times* argued, "*Chinese banks are increasingly reliant on funding sources that western peers used before the financial crisis, leading investors and analysts to warn that China's financial system could be vulnerable to a Lehman Brothers-style collapse. Their use of volatile wholesale borrowing to fund balance sheets has particularly worried analysts, who warn that banks could be left without the stability of a broad retail deposit base and unable to raise cash when most needed*."[61] In these circumstances, our thesis (Chapter 4) enables the market and policy makers to evaluate the impacts of the growth of shadow banking activities and the increase in the share of wholesale funds on the performance of Chinese banks and to assess whether the banking sector can maintain stable functioning under the new operating landscape.

[60] To illustrate, numerous Chinese banks issued interbank negotiated certificate of deposits (NCDs) to purchase high-risk, high-return wealth management products (WMPs) during the liquidity loosening cycle of 2014 to 2016. By heavily engaging in such risk-free interest rate arbitrage (as the revenue on bank WMPs was consistently higher than the funding cost of NCDs), banks realised profit gains (Luo et al., 2019).

[61] https://www.ft.com/content/1fcc5fd4-a719-11e6-8b69-02899e8bd9d1.

2.8 Conclusion

The Chinese banking system was once dominated by one single entity, the PBOC, which served as both the central bank and the sole commercial bank. Then, since 1979, China has taken an initiative to transform itself from a single banking sector to a multi-tiered banking sector that is made up of a central bank and various bank institutions with distinct ownership structures and some large banks. Accordingly, the Chinese banking system has been in the centre of an intense restructuring process over the past four decades. These restructuring reforms are widely believed as remarkable triumphs for China. It has promoted China's high economic growth rate, and the banking sector has developed rapidly in terms of both size and complexity. As stated, by 2017 the Chinese banking industry had become the largest in the world, with total assets amounting to US$39.9 trillion.

In this chapter, we have evaluated several major trends regarding Chinese banks' performance, business models and market structure and have conveyed concerns about the implications of these trends for the efficiency and stability of the banking system. With respect to changes in banking market capacity and structure, multiple capacity proxies, such as bank asset size and bank deposit value, indicate a rapid growth of the Chinese banking market in recent years. In addition, the striking decline in the concentration of the banking industry points to a better competitive environment among banks. This has been due to public listing of major banks during the past two decades and the introduction of foreign banks in the domestic market.

In terms of trends in banking performance, Chinese banks' earning ability has worsened across all banking segments and business models. This reflects issues such as the relatively low-inflation environment and high non-performing loans ratio, which have sharply undermined bank profitability in the Chinese market. Benefiting from a set of recapitalisation programmes, Chinese banks were no longer severely undercapitalised. Chinese banks' various capital ratios all meet the CBRC's minimum capital requirements. As for changes in business strategies and models, Chinese banks have displayed a tendency to restructure their operations away from less risky traditional activities towards more capital-intensive shadow banking activities. Meanwhile, an increasing number of Chinese banks have employed volatile wholesale financing to reduce the gap between deposit liabilities and assets. While these changes have contributed to profit growth in Chinese banks, they have involved a high level of bank risk and drawn regulators' concern. Overall, this chapter presents a contextual background of the Chinese banking system, which serves as a basis to the empirical estimation of cost economies and profitability and stability modelling that follow in Chapters 3 and 4.

Chapter 3

An Examination of the Size Dilemma in Chinese Banking: Scale Economies, Scale Efficiencies and Technological Change

3.1 Chapter Summary

Within the banking literature, there has been an interest in the relation between the size and the performance of financial institutions, and in particular the scale economies attained by banks (see, for example, Brown and Glennon 2000; Tadesse 2006; Wheelock and Wilson 2012; Davies and Tracey 2014). Moreover, since the 2008 global financial crisis (GFC), regulators and policymakers have looked again at whether and how to regulate bank size, as now it is believed that larger banks could destabilise the entire financial system through contagion. That is, in the highly interconnected financial industry, stress on one part of the system imposed by large banks in financial trouble can be transmitted to other parts, resulting in enormous reductions in economic output or even a recession for the real economy (Bongini, Nieri and Pelagatti, 2015).

This has brought attention to the complexity of large systemically important banks and raised a policy debate about whether a size cap should be imposed on banks (Grammatikos and Papanikolaou, 2018). The incentive for this supervisory action has been to limit the negative externalities associated with the failure of 'too big to fail' banking institutions. However, this debate seems largely to have overlooked the evidence that large banks can also generate positive externalities – large-scale operations enable banks to exploit significant scale economies and the resultant cost savings can be passed onto consumers in the form of more efficient intermediation and thus lower prices (Beccalli, Anolli and Borello, 2015). In this chapter, we examine the costs of imposing a size cap on banks – such constraints on banks' ability to realise economies of scale, with consequent net social loss.

In light of the policy debate over ‘too big to fail’, we examine evidence of scale economies for the Chinese banking industry over 2005-2015. Specifically, scale elasticity, scale efficiency, technological change and determinants of economies of scale are thoroughly examined in a sample of Chinese banks. The remainder of this chapter is structured as follows: section 3.2 gives a brief introduction to the chapter, while section 3.3, in presenting the theoretical background, links size effects to the argument regarding ‘too big to fail’ and offers the rationale for our study in light of the literature on economies of scale. Section 3.4 presents the empirical framework with respect to estimations of cost economies in the Chinese banking sector, including model specifications, sample and data collection, variable description and summary statistics. What follows in section 3.5 and section 3.6 are the presentation and discussion of the empirical results, while section 3.7 concludes this chapter and offers policy recommendations.

3.2 Introduction

During the GFC, majority of troubled large US banks and their UK counterparts were bailed out by their respective central banks and/or governments. For example, in October 2008, the Royal Bank of Scotland (RBS) was bailed out by the British government to the tune of £45 billion (from a total £50 billion bank rescue package) to save it from collapsing[62]. Of this sum, £20 billion was raised from the Bank Recapitalisation Fund; £5 billion was in preference shares and a further £15 billion was issued as ordinary shares. Other than the RBS, another sole major recipient of this rescue plan was Lloyds TSB; other primary troubled banks such as HSBC, Barclays, Nationwide, and Standard Chartered chose to opt out from this capital injection scheme[63]. In total, Lloyds TSB with Halifax Bank of Scotland received £17 billion in injections, where half were preference shares and the remainder ordinary shares (Bennett and Kottasz, 2012).

The above bail-out examples in the UK banking market were closely followed by the rest of Europe. On 14 October 2008 the US government announced a US$250 billion Capital Purchase Program to buy shares in a wide variety of banks in an attempt to enhance market liquidity and stabilise the market (Papanikolaou, 2018). The money came from the earlier-approved US$700 billion Troubled Asset Relief Program (TARP)[64].

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[62] RBS was the largest bank globally by total assets in the year 2008, and had a wide-ranging portfolio of financial assets when it had to be bailed out by the UK government. It was thought at the time that its US subsidiary, Greenwich Capital Investment Corporation, had a dangerous level of subprime assets. In 2013, the SEC fined RBS 180 million dollars for misleading investors in the subprime market. In the US, the Countrywide Financial Corporation sold its large number of sub-prime mortgages in order to limit the contagion effects when it was bought out by the Bank of America after the US government had already issued 45 billion dollars to protect it against losses of over 100 billion dollars in its assets.

[63] Bank participation in the 2008 bank rescue plan varied according to need. For example, HSBC announced that "*it was injecting £750m of capital into the UK bank and therefore has no plans to utilise the UK government's recapitalisation initiative as the bank remains one of the most strongly capitalised and liquid banks in the world*". Similarly, both Barclays and Standard Chartered Bank were declined government support in order to maintain their controlling shares; the former raised its own capital from private investors and the latter received injections from its subsidiaries.

[64] On 3 October 2008, the Troubled Asset Relief Program (TARP) was initiated and signed into law by President George W. Bush with the approval of the Emergency Economic Stabilization Act. Originally, the TARP allowed the US Treasury a total of US$700 billion purchasing power to buy illiquid mortgage-backed securities and other impaired assets from key institutions in a bid to mitigate foreclosures in the wake of the GFC and restore liquidity to the money markets. Then the Dodd-Frank Wall Street Reform and Consumer Protection Act announced a US$250 billion Capital Purchase Program on 14 October 2008,

This US rescue package was slightly different from its UK counterpart – the TARP was mainly intended to prevent failures of large US banks by purchasing their massive illiquid mortgage-backed securities, which could no longer be sold in the secondary market. Eight large American banks, i.e., Citigroup, JP Morgan, Morgan Stanley, Bank of America, Bank of New York Mellon, State Street, Goldman Sachs and Wells Fargo, were offered US$105 billion in capital injections by the Treasury from TARP funds during the crisis[65].

Bayazitova and Shivdasani (2012, page 377) point out that "*both for the US and UK, strong banks opted out of participating in capital purchase element and that equity infusions were provided to banks that posed systemic risk, faced high financial distress costs, but had strong asset quality*". It should be noted that following the collapse of Lehman Brothers, the Federal Reserve gave separate aid to American International Group (AIG) in an effort to avoid further catastrophe in the financial market that could arise from the insolvency of AIG. On four separate occasions, the aid increased from an initial proposal of a US$85 billion credit line (direct from Fed) to a commitment of approximately US$182 billion between the Fed (US$112.5 billion) and the Treasury (US$69.84 billion from TARP funds). Those authorities' efforts to save 'too big to fail' banks did help to stabilise the banking system and restore credit for individuals and businesses during the crisis[66] (Song and Uzmanoglu, 2016).

In addition to the bail-out, governments also encouraged mergers among troubled banks as another strategy to address insolvency, which led to a wave of merger and acquisition (M&A) activities across the world banking industry, such as Bank of America

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further aiming to stabilise the financial system.

65 As a payback, those banks were requested to pay the government a 5% dividend that would increase to 9% in 2013, a requirement that encouraged banks to purchase back their shares within five years.

66 With respect to the TARP, by 3 October 2010, Bayazitova and Shivdasani (2012, page 381) indicate that "*US$245 billion went to stabilize banks, US$27 billion went to programs to increase credit availability, US$80 billion went to the US auto industry (specifically, to GM and Chrysler), US$68 billion went to stabilize AIG, and US$46 billion went to foreclosure prevention programs, such as Making Home Affordable…. As of December 2013, the Treasury wrapped up TARP and the government concluded that its investments had earned more than US$11 billion for taxpayers"*. This government rescue package did make contributions to prevent further failures in the US economy and restore its economic growth.

with Merrill Lynch, Chase and Bear Stearns, and Wells Fargo and Wachovia in US banking. Indeed, a large number of failure-based mergers occurred during the crisis in terms of large banks taking over smaller struggling banks. However, after the GFC, these large banks continued to increase their size via M&A activities, resulting in many of the biggest banks getting even bigger. Those banking giants are much bigger today and have become oligopolies that control a huge market share of the entire US banking industry.

Baily et al. (2015, page 9) suggest that "*as of July 2015, the 12 largest banks now control 70% of all bank assets. Their favourite tool derivatives were taken away by the Dodd Frank laws, but they cleverly got derivatives back by including them in a bill to fund the government. And derivatives again backed by Federal Deposit Insurance Corporation, so banks are ready to gamble again.*" Similar patterns are seen in the Chinese banking sector. Like their US counterparts, the Chinese Big Four[67] also took over several failed banks as a response to the GFC and then actively employed M&A as a strategic growth model to increase their global presence. For instance, the asset growth of ICBC equalled CNY176,456 trillion in 2011, CNY210,684 trillion in 2014 and CNY256,710 trillion in 2017. It is unknown whether such growth could increase costs due to diseconomies of size – the question we answer in this chapter. That is, it is not known whether such large banks are less efficient and under normal competitive conditions would fail but are not allowed to do so because of their large size and interconnectedness.

It is increasingly posited that some banks are too big to fail (TBTF) and should be split up (see, for example, Demirgüç-Kunt and Huizinga, 2013; Oliveira, Schiozer and Barros, 2015; and Górnicka and Zoican, 2016). Indeed, in the GFC the stresses spread rapidly and extensively across the whole system when Lehman Brothers failed on 15th September 2008. The failure of these institutions, the so-called global systematically

[67] They are the four largest state-owned banks – Industrial and Commercial Bank of China (ICBC), Bank of China (BOC), China Construction Bank (CCB) and Agricultural Bank of China (ABOC) – see page 24 of Chapter 2. Aggregated assets of these four institutions accounted for approximately 46% of China's total banking assets in 2018 (Fang et al., 2019).

important banks (G-SIBs), threatens the functioning and stability of the system. Accordingly, international regulators such as BIS have sought to find out which huge international institutions are deemed TBTF by national regulators[68]. For instance, there have been intra-country analyses by domestic regulators to find out who are the G-SIBs in their countries, such as the Federal Reserve and O-SIIs, published annually by the European Banking Association.

Despite all the pressure, as discussed, large Chinese banks have got much bigger in terms of total assets and market capitalisation in the last decade. There are worries that this might make those banks more vulnerable and that the issue of TBTF will need to be urgently examined. To address these concerns, this chapter looks at the scale economies of Chinese banks – a comprehensive cost function based on a translog specification with share equations is estimated, and scale efficiency is then cross-examined with scale elasticity. Our analysis is also expected to determine whether large Chinese banks are experiencing cost advantages and whether this cost strengthening is due to technological scale economies or TBTF subsidies. Moreover, we investigate the underlying technological progress of the Chinese banking system in an attempt to shed light on the logic of the ongoing trend for consolidation within the banking industry.

In general, scale economies for banks are investigated through economic research into the microeconomic cost and production technologies in the banking system. However, Brown and Glennon (2000) assume that "*to the extent that researchers can identify a common technology, research results based on the identification of that technology may be inferred to the industry*" (page 1591). Accordingly, this chapter first partitions the full sample of banks in the study by asset size, as it is a widely held view that size is highly related with banks' funding and investment strategies, in the sense that size indicates a difference in banking activities (see Berger and Humphrey, 1991; Evanoff and Israilevich 1991; Altunbas, Evans and Molyneux, 2001; and Davies and Tracey,

[68] As defined by the Financial Stability Board (2009, page 45), systemic risk refers to "*a risk of disruption to financial service that is i) caused by an impairment of all or parts of the financial system and ii) has the potential to have serious negative consequences for the real economy*". It is a widely accepted definition.

2014). Therefore, asset size is commonly used as a proxy for product mix to segment the system into groups, where banks in the same group are likely to employ similar production technologies.

In recent years, an increasing number of studies (e.g., Dias and Ramos, 2014; Ayadi et al., 2016) have questioned size alone as an adequate categorising criterion since they report that dividing the sample by size of assets produces groupings in which the portfolio composition is similar across different categories (see detailed discussions of this issue in section 3.5.4). While segmenting banks according to size, this chapter also partitions the sample of banks into clusters (with the help of a clustering technique) based on their funding and investment activities. That is, we estimate clusters in terms of product mix, and thus allocate banks with similar production technology into the same natural clustering group. To the author's best knowledge, our study is the first empirically to identify differences in the production technologies among Chinese banks[69].

A further and more substantial part of our analysis in this chapter follows Simper et al. (2017) in presenting estimation results – based on generated clusters – but also analysing how the choice of risk proxies (i.e., equity, non-performing loans and loan loss provision) impacts upon the cost estimates of Chinese banks. Specifically, Hughes and Mester (2013) argue that if managers' risk preferences are omitted when modelling bank costs, the way costs vary with outputs show substantial changes due to systematic differences in risk-taking among banks. Following this assumption, the evaluation of scale economies is made more complex by taking account of risk-taking. A larger scale of operation brings greater diversification for banks, and not only offers economies of scale but also motivates banks to build on additional risk. This risk could obscure the underlying scale economies and result in biased estimates of them.

Our analysis contributes to the literature as one of the few empirical studies that

[69] Above two discussed grouping standards, by asset size and by portfolio composition, are detailly explained in section 3.5.3 and section 3.5.4 below. They are employed in this chapter for the purpose of allocating sample banks into categories for an in-depth comparison analysis.

captures risk in the bank production process by incorporating risk management variables into the cost specification of sample banks. More significantly, unlike previous research, such as Boateng, Huang and Kufuor (2015) and Hou et al. (2018), we include three selected risk factors separately and in different combinations (see Table 3.12), then utilise the Li test proposed by Li (1996, 1999) to determine which risk term should be added when considering the best fitted cost function with respect to the efficiency of the Chinese banking industry. Finally, a dynamic panel data regression is estimated for the evaluation of determinants of scale economies amongst Chinese banks, with the aim of inspecting whether different business models and risk-taking features affect the realisation of economies of scale in the Chinese banking market.

Analyses of the determinants of scale economies have generally been applied to the manufacturing and energy industries (e.g., You, Chen and Holder, 2010; Subrat and Kunal, 2012; Foster, 2015; and Klinke, 2018); few empirical studies focus on the banking industry (see Bertay, Demirgüc-Kunt and Huizinga 2013; Beccalli, Anolli and Borello 2015). Following Beccalli, Anolli and Borello (2015), to isolate the impacts of risk-taking features, variation in the business model and TBTF status on the realisation of scale economies in banking, we propose a dynamic panel data regression. In addition, a dynamic system generalised method of moments (GMM) estimator is used here to account for the dynamic nature of the examined economies of scale.

3.3 Theoretical Background

3.3.1 Review of Related Banking Studies

Around the world, the banking industry has been at the centre of a series of recent financial crises, and the role that bigger banks have played and the latest supervisory recommendations have directed renewed focus on the issue of scale economies in banking studies (e.g., Wheelock and Wilson, 2012; Hadad et al., 2013; Hou, Wang and Li, 2014; Davies and Tracey, 2014; and Psillaki and Mamatzakis, 2017). These studies, though, have mainly looked at advanced economies. Berger, Hanweck and Humphrey

(1987) is one of the earlier scholars to address the issue of scale economies within banking. His paper employs a simple quadratic equation of the log of total costs regressed on the log of total assets of all US state banks for the sample period of 1979 to 1984. It finds increasing returns to the cost for banks in the group with highest average costs, and the empirical results suggest that larger banks do not have competitive advantages over smaller banks, as no evidence of scale economies is found for either smaller or larger banks.

A later study by Simper (1998) investigates the scale economies of UK building societies over 1987 to 1992. In his paper, the whole sample was split into four equal quartiles according to banks' asset size. Significant economies of scale are found when sample banks are pooled together. However, for banks in the highest quartile (banks with the highest average asset size), they enjoyed scale economies from the year 1987 and then diseconomies of scale set in along with the later recession in UK. Above two studies laid the foundation for this research field. Then, different estimation approaches have been employed by academia to modelling scale economies in banking. For instance, adopting a dataset of US commercial banks, Brown and Glennon (2000) find evidence of scale economies for smaller US banks during 1990 to 1991 through the estimation of an seemingly unrelated cost regression.

More importantly, they propose a hypothesis that the banking industry is composed of individual banks that use different production technologies. Given this assumption, other than grouping sample banks based on size indicator, their study utilises clustering analysis to partition the sample into six different clusters. Banks are identified and grouped to reflect similar production process within groups but distinct technologies across groups as defined by the strategic conduct (i.e., funding and investment activities) of sample banks. It draws the conclusion that "*banks in different clusters employ production processes that feature different degrees of substitutability between factors of production, and that the estimates of input substitutability for those groups look quite different from those estimated based on the full population of commercial banks*" (Brown and Glennon; 2000, page 1591).

Harimaya (2008) analyses the scale and scope economies of trust businesses of the Japanese banking industry between 1994 and 2003. This study was conducted under the implementation of a series of deregulation reforms in Japanese banking and the author was interested to explore the effects of the new non-traditional banking activities (i.e., trust businesses in his paper) on the cost structure of Japanese banks. The standard translog cost function is selected, and significant scale economies are observed for sample banks across all asset size levels. However, product-specific scale economies are not evidenced for trust businesses in the sample. Furthermore, insignificant signs are obtained for cost complementarities in almost all the pairwise combinations of the products, indicating that entering into the trust business produces no cost reduction for Japanese banks.

A recent paper by Wheelock and Wilson (2012) offers a new nonparametric estimation of ray scale and expansion path economies of scale of US banks based on a cost model. Instead of employing previous limited sample or the restrictive parametric assumption, their study adopts local polynomial estimator and data on all US banks over the period of 1984 to 2006. The empirical findings show that sample banks exhibit substantial increasing returns to scale throughout the tested period. This may explain the growth in US bank average size and that the advantage of US banks exploiting scale economies seems to continue unless checked by interventions from supervisors. Nevertheless, post the GFC, Hughes and Mester (2013) revisit the US banking but in the purpose of assessing the cost and competitive implications of breaking up the largest banks into smaller banks.

That is, in the view of large banks pose systemic risks on the financial system, their study examines whether large size offers any cost benefits to the economy and, if so, whether these benefits are driven by TBTF subsidies or technological scale economies. They estimate scale economies of the US 842 top-tier bank holding companies during 2007, and for robustness, also use the US 1,855 top-tier and 856 top-tier bank holding companies in 2003 and 2010 as the model sample (also for an intention of examining the differences prior to and post the GFC). The paper finds "*evidence of large-scale economies at smaller banks and even larger economies at large banks…these measured* *scale economies do not result from the cost advantages large banks may derive from too-big-to-fail considerations. Instead, they follow from technological advantages, such as diversification and the spreading of information costs and other costs that do not increase proportionately with size"* (page 584).

As stated above, most of these studies have examined the advanced economies, and few have focused the Chinese banking industry. One of the earliest was by Fu and Heffernan (2007), who analyse scale economies in Chinese banking during the financial reform period of 1985 to 2002. The sample period is partitioned into two phases, the period of 1985-1992 is considered to be the first stage of reform and the year of 1993-2002 is deemed as the second phase of reform in their research. The empirical findings show that majority of Chinese joint-stock banks exhibit constant returns to scale throughout the full sample period. None scale economies are observed for these banks even during the second stage of reform which allows them to substantially expand their operations from regional to national wide. For Chinese state-owned banks, they present diminishing returns to scale over the first phase of reform and constant returns to scale in the second stage of reform.

In line with what have been recorded by Fu and Heffernan (2007), a later research by Meslier, Tacneng and Tarazi (2014) report the presence of diminishing returns to scale for large state-owned Chinese banks across 2006 to 2012. By adding Hong Kong banks into the Chinese data, Feyzioglu (2009) finds that the overall banking industry operates at constant returns to scale. Whereas significant scale economies are found for banks with smaller asset size and diseconomies of scale are documented for larger sample banks. Hou, Wang and Li (2014) identify the product-specific economies of scale for Chinese banks regarding loans, other earning assets and off-balance sheet activities (i.e., three chosen outputs) over the period of 2001 to 2012. Their empirical findings point out that the level of scale economies for bank loans seems to be constant with the size of loans. While the realisation of scale economies for other earning assets increases as the volumes of other earning assets decrease. Besides, sample banks enjoy more scale economies by expanding off-balance sheet operations and these cost economies could be generated especially for non-state-owned Chinese banks.

Dong, Hamilton and Tippett (2014) investigate scale economies for Chinese banks over 1994 to 2007 by partition the full sample into eight groups according to banks' assets values. On average, they find evidence of economies of scale for the Chinese banking system when all sample banks considered as a whole. Reviewing the results of scale economies estimates of the eight different size groups, it reveals that smaller banks with total assets lower than CNY250 billion are able to enjoy significant economies of scale – proposing that these banks could gain cost savings through expansion of their production scale. However, such cost advantages decline with the increase of bank size, diseconomies of scale start to present for banks with assets exceed CNY500 billion. Furthermore, the degree of evidenced scale economies reduces over time, implying most sample banks altering their operation scales in order to obtain optimal operating efficiency.

Zhang et al. (2016), with reference to the period of 2001-2014, on average, reports constant returns to scale for sample banks, advising that no more cost economies can be attained from expansion of the whole Chinese banking system. Wang (2017) documents the existence of scale economies for Chinese national joint-stock banks over 2007 to 2014. It is the positive competition drives these banks to enhance the product diversification, operation efficiency and the quality of their services and products which in turn allow them to achieve economies of scale. Meanwhile, five Chinese state-owned banks exhibit decreasing returns to scale. Nonetheless, they have been gradually improving scale efficiency, given the values of scale economies estimates gradually approaching to constant returns to scale.

Previous banking literature also inspects determinants that may play a role in achieving economies of scale, either concerned with bank-specific characteristics or macroeconomic factors (e.g., Bossone and Lee, 2004; Lelyveld and Knot, 2009; Bertay, Demirgüç-Kunt and Huizinga, 2013; and Beccalli, Anolli and Borello, 2015). Beccalli, Anolli and Borello (2015) suggest that a higher extent of economies of scale would be obtained if banks' business models more oriented toward securities operations with lower Tier 1 regulatory equity and higher liquidity. Besides, they document that TBTF banks tend to realise more scale economies. What have been found in an earlier study by Bertay, Demirgüç-Kunt and Huizinga (2013) support above assumption by showing that investment banking operations impose significantly positive effects on the realisation of scale economies in banking. They further argue that larger economies can be attained by banks in bigger financial systems compared to those in smaller markets.

In most cases, older related banking empirical studies are likely to document evidence of economies of scale are widespread across banks with smaller size, and report either decreasing returns to scale or constant returns to scale for larger banks (see, for example, McAllister and McManus, 1993; Berger and Humphrey, 1994; Mitchell and Onvural, 1996; and Brown and Glennon, 2000). However, as reviewed above, recently, a small set of research evidence discovers the existence of scale economies for all asset levels. It should be noted that any future regulatory policy that implying downsizing of banks as well as structural reforms restrict the chances for banks to earn potential economies of scale in the industry. Therefore, to shed the light on the policy debate on regulatory initiatives that introducing explicit bank size restrictions, and to fill the gap of evidence on scale economies amongst Chinese banks over recent years, this chapter attempts to examine scale economies (and scale efficiency) of Chinese banks as well as to analysis whether distinct business models and risk-taking of banks affect their capacity to attain economies of scale.

In addition, bank technological progress is also addressed in this chapter for the aim of interpreting the nature of scale economies in the industry. Over the last few decades, the Chinese banking system has undergone a series of unprecedented and sustained transformations and developments, some of the notable factors contributing to those changes are financial liberalisation and increased competitions in the financial market[70] (Wheelock and Wilson, 2012). Meanwhile, in the current decade, Chinese banks are considered to be one of the fastest growing banking sectors in the world, given China now runs four of the world's five largest banks (by assets) since 2015 (Garrido and

[70] For a more detailed discussion on these transformations and developments, see section 2.3.

Chaudhry, 2019)[71]. Analysing the underlying technological progress of the Chinese banking system enables us to explain the recent increase in the size of the sector.

3.3.2 Notion of 'Too Big to Fail' and Identification of 'Too Big to Fail' Banks in China

As discussed, the literature regarding scale economies in banking is extensive. However, the GFC highlighted a concern about whether the benefits of large size outweigh potential costs in terms of systemic risk. Besar et al. (2011) argue that although a single bank's own portfolio may not represent a systemic risk, the interconnectedness of global banks with other financial institutions can bring instability to the market. The literature suggests that those large systemically important banks generally are perceived to be too big to fail. The distress or failures of these banks on the one hand are extremely costly and challenging to resolve due to their huge size, complexity and widespread international footprints, and on the other hand can spread systemic risk throughout the financial market and into the rest of economy (e.g., BIS, 2013ab; Boyd and Heitz, 2016; Zedda and Cannas, 2017; IMF, 2017a; Luciano and Wihlborg, 2018; and Cai et al., 2018).

According to BIS (2013a), global systemically important banks, G-SIBs, are deemed to be 'too big to fail' (TBTF) and 'too interconnected to fail' due to:

- their huge size;
- their complexity;
- lack of readily available alternative financial institution infrastructure or substitutes for services they offer;
- their active cross-jurisdictional activity; and
- their global interconnectedness.

The above 5 points have been employed by BIS to assess the systemic importance of G-SIBs; see Table 3.1 for a detailed summary of the interpretation of these 5 criteria. The

[71] See the detailed discussions with respect to the rapid expansion in the asset size of Chinese banks in section 2.5.

table explains the rationale for how these banks can generate 'too big to fail' risks for banking stability. This chapter now explores these issues in the context of viewing financial stability on a system-wide level. On the one hand, the risk profiles and resilience of each individual bank do affect system stability through intra-group connections, and it is no surprise that size and balance sheet activities can be incorporated as a key measure of systemic importance. It is generally believed that the larger (greater) the banks' size (complexity), the more difficult it is to resolve potential failures. This is in consideration of their structural, operational and business modelling complexity[72].

More significantly, the more widespread spill-over effects that arise from distress in a bank's enormous on- and off-balance sheet operations can lead to a sudden collapse in market confidence. As discussed by Varotto and Zhao (2018), this can cause later 'fire sales' of assets and a liquidity freeze in the interbank and capital markets. These were two influential contributors to the propagation of loss contagion across banks in the case of the GFC. Interestingly, Laeven, Ratnovski and Tong (2016) suggest that size was normally considered to be the paramount standard of measuring the systemic importance of a bank up until the GFC, but that crisis revealed that systemic risk might also materialise from banking network interconnections[73]. That is, systemic stability can be notably affected by potential direct (e.g., via contractual obligations) or indirect (e.g., via 'fire sale' externality, information contagion or common exposures) crisis contagion effects which occur with the failure of G-SIBs.

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[72] For example, Kaufman (2013) argues that failures of very large banks that are highly interconnected are considered to be more disruptive to the financial system and broader economy and hence necessitate a bail-out to prevent failure. This 'too big to fail' status incentivises certain banks to deliberately use leverage and unstable funding and to take positions that are excessively risky. In addition, large banks tend to be more organisationally complex, having more subsidiaries than small banks, which suggests that they could create more systemic risk. Moreover, Laeven et al. (2014) point out that funding (measured by the share of deposits in total liabilities) for large banks is more fragile than for small ones.

[73] See a detailed summarisation and interpretation of possible systemic risk transmission channels in Mensah and Premaratne (2017) and Aldasoro, Gatti and Faia (2017). To summarise, there are four common contagion channels in which systemic risks can emerge:

- financial institution infrastructure;
- over-the-counter derivative, collateral and security markets;
- short-term funding and deposit markets; and
- common exposures.

It has been shown that financial distressed G-SIBs will transmit their losses to other banks when they fail, and the spread of these losses fuels contagion as turmoil spreads throughout the financial system and into the economy. Accordingly, in order to reduce the costs related to these banks, the Basel Committee on Banking Supervision has introduced five-indicator appraisal framework (presented above) to identify G-SIBs and has implemented a series of additional regulatory control on G-SIBs to internalise their externalities (Bongini and Nieri, 2014). Table 3.2 presents the updated G-SIBs list and those banks' allocated capital bucket information[74]. These 30 TBTF banks yield evaluation scores that surpass the cut-off point set by BIS and are deemed to be G-SIBs.

[74] The recent G-SIBs list based on the Financial Stability Board classification indicates that a larger capital buffer is necessary for those banks under the new regulatory environment. That is, 30 named G-SIBs, including JP Morgan Chase, Bank of America, Bank of China and Agriculture Bank of China, are the banks that subject to BIS's higher loss absorbency requirements. The level of required additional capital varies in accordance with their corresponding estimation scores of systemic importance – the higher the score, the higher the level of additional capital buffer imposed on G-SIBs (BIS, 2013a). The Bank of China, for example, is allocated to bucket 2, indicating that it needs to hold a higher capital ratio, that is, at least 1.5% higher than the minimum level of regulatory capital requirement set by Basel III. Note that higher buffers could be enforced on the top of this bucket level by each national jurisdiction to address their varied risk levels.

Table 3.1: BIS five-indicator measurement approach.

Category (and weighting)	Individual indicator (and weighting)	Description of each category
Size (20%)	➢ Intra-financial system assets (6.67%) ➢ Intra-financial system liabilities (6.67%) ➢ Securities outstanding (6.67%)	**Positive** relationship – A bank's distress or failure is more likely to damage the global economy or financial markets if its activities comprise a large share of global activity. The larger the bank, the more difficult it is for its activities to be quickly replaced by other banks and therefore the greater the chance that its distress or failure would cause disruption to the financial markets in which it operates.
Complexity (20%)	➢ Notional amount of over-the-counter (OTC) derivatives (6.67%) ➢ Level 3 assets (6.67%) ➢ Trading and available-for-sale securities (6.67%)	**Positive** relationship – The more complex a bank is (its business, structural and operational complexity), the greater are the costs and time needed to resolve the bank.
Financial institution infrastructure (20%)	➢ Assets under custody (6.67%) ➢ Payments activity (6.67%) ➢ Underwritten transactions in debt and equity markets (6.67%)	**Positive** relationship – The greater a bank's role in a particular business line, or as a service provider in underlying market infrastructure, the larger the disruption will likely be following its failure.

Cross-jurisdictional activity (20%)	➢ Cross-jurisdictional claims (10%) ➢ Cross-jurisdictional liabilities (10%)	**Positive** relationship – The international impact of a bank's distress or failure would vary in line with its share of cross-jurisdictional assets and liabilities. The greater a bank's global reach, the more difficult it is to coordinate its resolution and the more widespread the spill-over effects from its failure.
Interconnectedness (20%)	➢ Intra-financial system assets (6.67%) ➢ Intra-financial system liabilities (6.67%) ➢ Securities outstanding (6.67%)	**Positive** relationship – Financial distress at one institution can materially increase the likelihood of distress at other institutions given the network of contractual obligations in which these firms operate. A bank's systemic impact is likely to be positively related to its interconnectedness vis-à-vis other financial institutions.

Source: BIS (2013a)

As expected, the Chinese G-SIBs are the Big Four. It is worth noting that the number of G-SIBs and their capital bucket allocations will change every year, in line with G-SIBs' changes on their balance sheet and changes in their behaviours in response to the incentive of the G-SIB framework as well as other aspects of Basel III and various national policies. BIS runs the test every year with new modulations and has annually produced an updated G-SIBs list since 2013. The evolution of Chinese G-SIBs is described in Table 3.3. Bank of China is the only included Chinese G-SIB across all lists due to the dominant role it plays in the foreign payment system[75]. Moreover, the Big Four were on the G-SIBs list five years in a row from 2015, a reflection of the expansion in systemic size. Industrial and Commercial Bank of China and Bank of China moved from bucket 1 to a higher bucket during 2016 and 2017 respectively, suggesting a further increase in the global presence of these two banks.

In addition to the Chinese G-SIBs, domestic systemically important banks, or D-SIBs, are identified as well in our study sample. We follow the PBOC's stress testing bank list, in which 15 listed Chinese banks[76] are so-called 'too big to fail' banks in China and are potential D-SIBs. They collectively represented roughly 61% of the total assets of the

[75] In Table 3.1, the provision of payment, underwritten and asset under custody services are employed by BIS to represent the financial institution infrastructure this indicator. Notably, this category plays a dominant role on the evaluation of systemic importance of sample banks and a cap is imposed to restrict its prominent impact. The leading role that this particular indicator plays in the determination of systemic importance of G-SIBs may explain the rationale of an interesting fact – which is among the Big Four, Bank of China is the only one that appears on all G-SIBs lists across 2013 to 2019 (see Table 3.3). Despite of its total on and off-balance sheet assets exposures remain the smallest among the group, Bank of China generates the highest systemic importance. This mainly attributes to the fact that Bank of China has been historically regarded as the state-designated specialised foreign trade and exchange bank within the Chinese banking sector (Diallo and Zhang, 2017). For example, payments settled through payment systems or correspondent banks by Bank of China are CNY432,865,206 at the end of year 2016. It is around 25% higher than the corresponding value of Industrial and Commercial Bank of China, roughly 40% higher than China Construction Bank and more than doubled compared to Agricultural Bank of China. In terms of global footprints, Bank of China displayed an aggregate cross-jurisdictional exposure of CNY 6,976 billion by the end of 2016 – this value is almost twice as large as Industrial and Commercial Bank of China, 3 and 5 times bigger than China Construction Bank and Agricultural Bank of China respectively. Clearly, the distress or failure of Bank of China (or either Chinese G-SIBs) can pose serious interruption to the market operation for foreign transactions and sharply reduce the liquidity flow in the interbank payment system. Besides, it is considerably pricy for customers to switch their services from failed bank to another bank and they will suffer massive losses if there is a bank run (Bongini et al., 2018).

[76] These banks are: the Big Four, Bank of Communications, China CITIC Bank, China Everbright Bank, China Merchants Bank, China Minsheng Banking Corporation, China Zheshang Bank, Hua Xia Bank, Industrial Bank, Ping An Bank, Postal Savings Bank of China, and Shanghai Pudong Development Bank.

whole Chinese banking system at the end of 2015 (PBOC, 2017). Then, following the quantitative approach proposed by Chen et al. (2014), the systemic importance of each identified D-SIB is examined here. Chen et al. (2014) follow the five-indicator measurement approach proposed by BIS but modify the choice of financial indicators, and develop a domestic framework for Chinese D-SIBs. Table 3.4 shows that the redesigned methodology is basically in line with the BIS framework. Major modifications lie in the chosen financial indicators that portray banks' systemic importance due to data availability and the transforming of the category 'cross-jurisdictional activity' to 'public confidence', which was regarded as 'domestic sentiment' in Buriak, Lyeonov and Vasylieva (2015).

Table 3.2: The Financial Stability Board's list of G-SIBs and their allocated capital buckets (2019).

Bucket	**Banks**
5 (3.5%)	Empty
4 (2.5)	JP Morgan Chase
3 (2%)	Citigroup; HSBC
2 (1.5%)	Bank of America; Bank of China; Barclays; BNP Paribas; Deutsche Bank; Goldman Sachs; Industrial and Commercial Bank of China; Mitsubishi UFJ FG; Wells Fargo
1 (1%)	Agricultural Bank of China; Bank of New York Mellon; China Construction Bank; Credit Suisse; Groupe Crédit Agricole; ING Bank; Mizuho FG; Morgan Stanley; Nordea; Royal Bank of Canada; Royal Bank of Scotland; Santander; Société Générale; Standard Chartered; State Street; Sumitomo Mitsui FG; UBS; Unicredit Group

Please refer to footnote 74 for the explanation of capital buckets.

Source: FSB (2019)

Table 3.3: The bucket allocation of Chinese G-SIBs.

Banks	2013	2014	2015	2016	2017	2018	2019
BOC	B1	B1	B1	B1	B2	B2	B2
ICBC	B1	B1	B1	B2	B2	B2	B2
CCB			B1	B1	B2	B1	B1
ABOC		B1	B1	B1	B1	B1	B1

Where BOC stands for Bank of China; ICBC is Industrial and Commercial Bank of China; CCB represents China Construction Bank and ABOC is Agricultural Bank of China.
Where B1 represents the capital bucket 1 and B2 denotes bucket 2 (see Table 3.2).

Source: Author's own calculations

This means, as shown in Table 3.4, the five categories of indicators adopted in our study to appraise a bank's systemic importance are: 'size', 'complexity', 'financial institution infrastructure', 'interconnectedness' and 'public confidence'. Consistent with the BIS methodology, all five categories are assigned an equal weight of 20%. As for sub-indicators, the total weight of a category (i.e., 20%) will be equally distributed to all sub-indicators in that category. For instance, there are three sub-indicators under the category of 'financial institution infrastructure' in our approach (see Table 3.4, column 'Approach for China'), each will be appointed a weight of a third of 20% (that is approximately 6.67%). Then the score on each sub-indicator is calculated as follows: (1) to divide individual bank amount by the aggregate amount across all 15 banks that are recognised to be TBTF; and (2) this calculated result is then weighted by the sub-indicator's weight. In this way, the final systemic importance score of a bank is the sum of weighted scores on all sub-indicators of this bank (there are nine sub-indicators under our measurement method), and such a score reveals the level of systemic importance of a bank in the banking system. The higher the score, the higher the level of systemic importance of a bank.

Correspondingly, the calculated systemic importance scores of 15 TBTF banks over the period of 2008 to 2015 are specified in Table 3.5[77]. It shows that the internationally

[77] It should be noticed that the PBOC only began stress testing on designated banks from 2008 – which means the bank list adopted by us can only be traced back to 2008 – even though our sample covers the

recognised Big Four have high systemic impact on Chinese banking, given that in total they accounted for 63.64% systemic importance of the entire industry in 2015, although this was down from 70.42% in 2005. Throughout 2008-2015, every year, the 6 state-owned commercial banks in total accounted for over 70% systemic importance of the whole banking sector. Meanwhile, the remaining 9 joint-stock banks were observed to present little domestic systemic importance. For example, the Industrial Bank was found to contribute only about 4.4% importance to the Chinese banking system in 2015, and China Zheshang Bank hardly imposed any systemic impact on Chinese banking over 2008-2015 with an average score of only 0.4%. Nevertheless, the collective systemic importance of these 9 banks kept increasing between 2008 and 2015 (their total score increased from 18% in 2008 to 25.6% in 2015). Such an increasing tendency indicates domestic systemic importance is distributed among the system more evenly.

Table 3.6 exhibits the yearly rankings of the 15 TBTF banks in terms of their systemic importance scores during 2008 to 2015. As shown, across this period, the four biggest systemic risk conveyors remained as the Big Four throughout. Among the Big Four, the Industrial and Commercial Bank of China (ICBC) is the single largest conveyor of systemic risk, accounting for 21.1% systemic importance of the whole system in 2008, and this was 18.8% in 2010, 20.4% in 2012, and 18.4% in 2015. Interestingly, Bank of China (BOC) accounted for roughly 13% systemic importance in 2015, ranking it fourth on the list; that figure represents a decline from around 17% in 2005, when it ranked third. However, BOC has been regarded as one of the G-SIBs and has made it onto the Financial Stability Board's list since it was first published in 2011, while ICBC has been on the list only from 2013. This reflects how different choices of financial indicators do produce discrepancies and/or global systemic importance does not necessarily equal domestic systemic importance. As stated above, BOC has long been considered to be one of the G-SIBs due to its high significance in both complexity and cross-jurisdictional activity dimensions, whereas our domestic method alters the 'cross-jurisdictional activity' to 'domestic sentiment' criteria which the other three banks of the Big Four would be benefit.

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period from 2005 to 2015.

In conclusion, in addition to the Big Four, Bank of Communications, Postal Savings Bank of China, Industrial Bank, China Merchants Bank, China Minsheng Bank, Shanghai Pudong Development Bank, China CITIC Bank, China Everbright Bank, Ping An Bank, Hua Xia Bank, and China Zheshang Bank are determined as 'too big to fail' banks in the Chinese domestic banking market in our sample. After the GFC, the costs and risks of TBTF bailouts have highlighted the debates concerning the role and benefits of size of banks and the impacts of public safety net subsidies that accrue with both size and complexity (He and Chen, 2016). This is particularly the case for China; IMF's Chinese financial system stability assessment report (2017) emphasises that Chinese TBTF banks call for more close monitoring due to their critical performance in the funding market. The report shows that there is an increasing concern among policymakers about the probability of these TBTF banks repeating the 'Lehman episode' as their wholesale borrowing increases.

Severe negative externalities related to the failure of TBTF banks are well recognised (Cubillas, Fernández and González, 2017). The moral hazard issue might arise when bank managers know that their institutions have TBTF status and able to accept undue risks because a government bailout will occur if needed (Altunbas, Binici and Gambacorta, 2018). Nonetheless, the financial, economic and social costs of such government interventions are fairly high (Bongini and Nieri, 2014).[78] In response, new banking regulations (e.g., Basel III) have sought to implement constraints on banks by requesting more liquidity and capital[79] and also to restrain riskier areas of operation – all of which curb banks' size[80]. The aim of these supervisory considerations has been to limit implicit TBTF subsidies; however, the policy dispute seems to have largely overlooked the evidence that large banks can also generate positive externalities. As

[78] Also see discussions in section 3.2.

[79] In accordance with Basel III requirements, proposed regulatory rules such as higher loss absorbency requirements and liquidity caps (liquidity coverage ratio and net stable funding ratio) offer systemically important banks motivations to shrink, given the high regulatory cost these TBTF banks may face. To illustrate, the US Vitter-Brown bill, under circulation in Congress, will require banks with more than US$500 billion in assets to maintain a minimum of 15% equity-to-asset ratio rather than the current 8%.

[80] There is also an on-going intense policy debate on the feasible implementation of explicit size restrictions in banking (see, for example, Fisher, 2013; Hughes and Mester, 2013; Davies and Tracey, 2014; and Beccalli, Anolli and Borello, 2015).

suggested by Beccalli, Anolli and Borello (2015, page 233), "*limiting the size of big banks could result in a net social loss if the restrictions inhibit banks' ability to realize potential scale economies that can be passed onto bank customers in the form of more efficient intermediation and therefore lower prices*".

Yet, as discussed, possible structural reforms and regulatory initiatives restricting bank size, to a certain extent, restrain the chances for banks to fully obtain scale economies. Therefore, one of the main objectives of this chapter is to find evidence of economies of scale for Chinese banks with large asset size and explore whether these scale economies are driven by technological progress or TBTF subsidies. This could provide empirical evidence for current regulatory discussions of downsizing in banking. With respect to our analysis of the significance of examining Chinese bank scale behaviour, we next present the basis of the estimation procedure and data employed.

Table 3.4: The indicator-based measurement approach for China (compared with the standard BIS approach).

Category (and weighting)	Standard BIS approach	Approach for China
Size (20%)	➢ Intra-financial system assets (6.67%) ➢ Intra-financial system liabilities (6.67%) ➢ Securities outstanding (6.67%)	➢ Total assets (20%)
Complexity (20%)	➢ Notional amount of over-the-counter (OTC) derivatives (6.67%) ➢ Level 3 assets (6.67%) ➢ Trading and available-for-sale securities (6.67%)	➢ Held-to-maturity securities (10%) ➢ Trading securities (10%)
Financial institution infrastructure (20%)	➢ Assets under custody (6.67%) ➢ Payments activity (6.67%) ➢ Underwritten transactions in debt and equity markets (6.67%)	➢ Residential mortgage loans (6.67%) ➢ Corporate and commercial loans (6.67%) ➢ Government securities (6.67%)
Cross-jurisdictional activity (20%)	➢ Cross-jurisdictional claims (10%) ➢ Cross-jurisdictional liabilities (10%)	Not included
Interconnectedness (20%)	➢ Intra-financial system assets (6.67%) ➢ Intra-financial system liabilities (6.67%) ➢ Securities outstanding (6.67%)	➢ Loans and advances to banks (10%) ➢ Deposits from banks (10%)
Deposits from banks (Public confidence)	Not included	➢ Total customer deposits (20%)

Source: BIS (2013a) and Chen et al. (2014)

Table 3.5: The calculated systemic importance scores of 15 TBTF banks over 2008-2015.

Banks	Types	2008	2009	2010	2011	2012	2013	2014	2015
ICBC	State-owned	0.211	0.199	0.188	0.211	0.204	0.193	0.187	0.184
ABOC	State-owned	0.149	0.179	0.150	0.145	0.160	0.161	0.165	0.167
CCB	State-owned	0.176	0.168	0.153	0.148	0.145	0.164	0.163	0.155
BOC	State-owned	0.168	0.160	0.163	0.155	0.139	0.132	0.132	0.130
BOCOM	State-owned	0.068	0.065	0.070	0.062	0.057	0.058	0.055	0.058
PSBC	State-owned	0.048	0.048	0.054	0.051	0.051	0.054	0.054	0.050
IB	Joint-stock	0.024	0.023	0.033	0.036	0.040	0.041	0.042	0.044
CMB	Joint-stock	0.035	0.036	0.037	0.033	0.036	0.037	0.039	0.042
CMSB	Joint-stock	0.024	0.023	0.028	0.030	0.038	0.031	0.036	0.037
SPDB	Joint-stock	0.020	0.024	0.035	0.036	0.034	0.034	0.032	0.035
CITIC	Joint-stock	0.029	0.030	0.029	0.036	0.029	0.032	0.031	0.034
CEB	Joint-stock	0.022	0.023	0.029	0.026	0.027	0.022	0.022	0.022
PAB	Joint-stock	0.009	0.009	0.011	0.011	0.017	0.019	0.019	0.019
HXB	Joint-stock	0.015	0.011	0.017	0.017	0.017	0.016	0.016	0.017
CZB	Joint-stock	0.002	0.002	0.003	0.004	0.004	0.005	0.006	0.007

ICBC: Industrial & Commercial Bank of China, ABOC: Agricultural Bank of China, CCB: China Construction Bank, BOC: Bank of China, BOCOM: Bank of Communications, PSBC: Postal Savings Bank of China, IB: Industrial Bank, CMB: China Merchants Bank, CMSB: China Minsheng Banking Corporation, SPDB: Shanghai Pudong Development Bank, CITIC: China CITIC Bank Corporation, CEB: China Everbright Bank, PAB: Ping An Bank, HXB: Hua Xia Bank, CZB: China Zheshang Bank.
State-owned: state-owned commercial banks, Joint-stock: joint-stock commercial banks.

Source: Author's own calculations

Table 3.6: The yearly rankings of 15 TBTF banks by systemic importance scores over 2008-2015.

Banks	Types	2008	2009	2010	2011	2012	2013	2014	2015
ICBC	State-owned	1	1	1	1	1	1	1	1
ABOC	State-owned	4	2	4	4	2	3	2	2
CCB	State-owned	2	3	3	3	3	2	3	3
BOC	State-owned	3	4	2	2	4	4	4	4
BOCOM	State-owned	5	5	5	5	5	5	5	5
PSBC	State-owned	6	6	6	6	6	6	6	6
IB	Joint stock	9	12	9	9	7	7	7	7
CMB	Joint-stock	7	7	7	10	9	8	8	8
CMSB	Joint-stock	10	11	12	11	8	11	9	9
SPDB	Joint-stock	12	9	8	8	10	9	10	10
CITIC	Joint-stock	8	8	11	7	11	10	11	11
CEB	Joint-stock	11	10	10	12	12	12	12	12
PAB	Joint-stock	14	14	14	14	13	13	13	13
HXB	Joint-stock	13	13	13	13	14	14	14	14
CZB	Joint-stock	15	15	15	15	15	15	15	15

ICBC: Industrial & Commercial Bank of China, ABOC: Agricultural Bank of China, CCB: China Construction Bank, BOC: Bank of China, BOCOM: Bank of Communications, PSBC: Postal Savings Bank of China, IB: Industrial Bank, CMB: China Merchants Bank, CMSB: China Minsheng Banking Corporation, SPDB: Shanghai Pudong Development Bank, CITIC: China CITIC Bank Corporation, CEB: China Everbright Bank, PAB: Ping An Bank, HXB: Hua Xia Bank, CZB: China Zheshang Bank.
State-owned: state-owned commercial banks, Joint-stock: joint-stock commercial banks.

Source: Author's own calculations

3.4 Research Design and Data

Having reviewed the rationale for examining scale performance in the Chinese banking industry, our study now moves on to discuss the empirical framework of our proposed estimations. First, section 3.4.1 discusses the translog cost function employed for the evaluation of scale economies, scale efficiency and technological progress of Chinese banks. Then section 3.4.2 discusses the dynamic panel data regressions utilised for the analysis of determinants of economies of scale in Chinese banking. Section 3.4.3 discusses the sample selection and data collection for our research, and describes all the variables for empirical estimation in this chapter. In section 3.4.4, summary statistics of these variables are presented.

3.4.1 Scale Performance Estimation – Cost Function

Our study follows Wheelock and Wilson (2012) and Bryce et al. (2015), and the cost function is defined as

$$lnTC_{it} = const + f(y_{it}, w_{it})\beta + \varepsilon_{it} \tag{3.1}$$

where $lnTC_{it}$ refers to the natural logarithm of total costs for the ith bank in year t, y_{it} is a vector of outputs for each sample bank in period t and w_{it} is a vector of bank input prices. While ε_{it} is an error term.

Further developing the general cost specification proposed above, a few functional forms are available, including the Cobb-Douglas function, semi-non-parametric Fourier-flexible function and translog (transcendental logarithmic) function. We are in favour of translog equation since it offers a flexibility that enables the tested banks' cost structures to be free from second-order property restrictions. This specification allows multiple inputs and outputs to be entered for estimation and accommodates the homogeneity of the data and relaxes the pre-requisite assumptions (Fang and Jiang, 2014). For instance, the translog function does not require perfect Allen elasticities of substitution. Moreover, it allows the correlation between bank inputs and outputs to move from linear to nonlinear. Hence, this so-called flexible functional form can be employed to produce the second-order approximation of the estimation of the production frontier, the estimation of Allen elasticities of substitution between production factors and/or the measurement of the total factor productivity dynamics.

Based on duality theory, when banks pursue cost-minimising behaviours, the above cost equation (3.1) which characterises the production technology of sample Chinese banks can be specified as:

$$\begin{aligned} lnTC_{it} = const &+ \sum_{n=1}^{3} \alpha_n \ln y_{nit} + \sum_{k=1}^{3} \beta_k \ln w_{kit} \\ &+ {}^{1}/_{2} \left[\sum_{n=1}^{3} \sum_{j=1}^{3} \sigma_{nj} \ln y_{nit} \ln y_{jit} \right. \\ &\left. + \sum_{k=1}^{3} \sum_{l=1}^{3} \gamma_{kl} \ln w_{kit} \ln w_{lit} + \sum_{n=1}^{3} \sum_{k=1}^{3} \delta_{nk} \ln y_{nit} \ln w_{kit} \right] \\ &+ \eta_1 T + {}^{1}/_{2}\, \eta_2 T^2 + \sum_{n=1}^{3} \theta_n \ln y_{nit}\, T + \sum_{k=1}^{3} \tau_k \ln w_{kit} T \\ &+ \varepsilon_{it} \end{aligned} \tag{3.2}$$

where $lnTC_{it}$ denotes the natural logarithm of total costs (i.e., the sum of personnel expenses, total interest expenses and other operating expenses in our case) for the ith bank during year t. The definition of chosen bank inputs and outputs are given in section 3.4.3 (see Table 3.8). $\ln y_{nit}$ and $\ln w_{kit}$ are the log of the nth output and log of the kth input price for the ith bank at time t. T is the time trend. It should be noticed that time trend variables are included in a bid to account for changes in technology over the sample period. When risk management control variables are included in regression (3.2), the equation becomes:

$$\begin{aligned} lnTC_{it} = const &+ \sum_{n=1}^{3} \alpha_n \ln y_{nit} + \sum_{k=1}^{3} \beta_k \ln w_{kit} \\ &+ {}^1\!/_2 \left[\sum_{n=1}^{3} \sum_{j=1}^{3} \sigma_{nj} \ln y_{nit} \ln y_{jit} \right. \\ &\left. + \sum_{k=1}^{3} \sum_{l=1}^{3} \gamma_{kl} \ln w_{kit} \ln w_{lit} + \sum_{n=1}^{3} \sum_{k=1}^{3} \delta_{nk} \ln y_{nit} \ln w_{kit} \right] \\ &+ \eta_1 T + {}^1\!/_2\, \eta_2 T^2 + \sum_{n=1}^{3} \theta_n \ln y_{nit}\, T + \sum_{k=1}^{3} \tau_k \ln w_{kit} T \\ &+ \varphi_1 lnz_{it} + {}^1\!/_2\, \varphi_2 lnz_{it}^2 + \sum_{n=1}^{3} \rho_n \ln y_{nit}\, lnz_{it} \\ &+ \sum_{k=1}^{3} \zeta_k \ln w_{kit} lnz_{it} + \varepsilon_{it} \end{aligned} \tag{3.3}$$

where lnz_{it} refers to the natural logarithm of the risk management variables considered, namely equity, non-performing loans and loan loss provision, for the ith bank at time t. The rationale for the incorporation of these risk control variables is given in section 3.2 and section 3.4.3.

Our preferred estimation technique is the seemingly unrelated regression. This approach is selected as it offers more efficiency for estimation if factor share equations are estimated simultaneously. This is particularly the case for our Chinese sample, as a small degree of freedom will be left with numerous parameters estimated (Chen and Lin, 2016). Thus, cost shares are jointly estimated with the cost specification (3.3) through seemingly unrelated iterative regressions. Specifically, the cost shares of the various banking outputs are demand functions for the inputs, and they can be estimated by differentiating equation (3.3) in terms of input prices and using Shepard's lemma. Following Zellner (1962) and Brown and Glennon (2000), the share equation is:

$$S_k = \frac{\partial lnTC_{it}}{\partial lnw_{kit}} = \beta_k + \sum_{l=1}^{3} \gamma_{kl} \ln w_{lit} + \sum_{n=1}^{3} \delta_{nk} \ln y_{nit} + \tau_k T + \zeta_k lnz_{it} \tag{3.4}$$

Next, the system singularity of the share function is highlighted by imposing homogeneity and symmetry restrictions on share equations during estimation. That is:

$$\sum_{k}\beta_k = 1, \qquad \sum_{kl}\gamma_{kl} = 0, \qquad \sum_{nk}\delta_{nk} = 0 \qquad (3.5)$$

Under such restrictions, one share price should be omitted from the equation. That is, one of the bank inputs, i.e., other operating expense, is treated as the reference cost share, and the remaining two shares are normalised based on other operating expenses.

Having defined the cost specification (3.3), to evaluate the economic usefulness of this model, the violations of regularity conditions, i.e., monotonicity and concavity, are examined. The monotonicity condition requires that all inputs in the production equation are monotonically increasing, as stipulated by microeconomic theory (Harimaya, 2008). According to Henningsen and Henning (2009), "*the rationale for the monotonicity assumption is as follows: if (in rare cases) there is indeed a negative technical input–output relationship (e.g., too much fertilizer burns the crops), a wise manager would simply leave a part of the input unused (e.g., leave some of the fertilizer in the bag). Therefore, increasing the (unused) quantity of this input would leave the output (at least) unchanged*" (page 218).

For function (3.3), the monotonicity condition can be expressed as following form since all inputs and outputs require positive partial derivatives:

$$\frac{dTC}{dy_n} > 0, \qquad \frac{dTC}{dw_k} > 0 \qquad (3.6)$$

Except for the examination of the monotonicity assumption, as mentioned, concavity is also checked to ensure that all inputs are convex and thereby reducing marginal rates of technical substitution will be generated for our estimation (Baum and Linz, 2009). Following Brown and Glennon (2000), the concavity is estimated by the Allen partial elasticity and Allen own price elasticity, as specified below (in which the value must be negative):

$$(\gamma_{kl} + S_k S_l)/S_k S_l \tag{3.7}$$

$$(\gamma_{kk} + S_k^2 - S_k)/S_k \tag{3.8}$$

Equation (3.4) gives the estimation of γ_{kl} and S_k is the share of costs of the kth input.

The significance of monotonicity and concavity conditions has largely been overlooked in previous bank cost analyses (e.g., Tadesse, 2006; Hou, Wang and Li, 2015). In order to fill this gap, our study thoroughly examines these model restrictions. Once the robustness of the proposed model is confirmed, the scale elasticity, in terms of the proportional increase in all three outputs, is proxied by ray scale economies (SE_{it}) and is generated by

$$SE_{it} = \sum_{k=1}^{3} \frac{\partial lnTC_{it}}{\partial lnQ_{it}} \tag{3.9}$$

where Q represents the quantity of bank outputs. The concept of scale economies suggests that bigger banks have the ability enjoy inherent cost advantages compared with smaller banks. Economies of scale reflect how costs change with outputs (Badunenko and Kumbhakar, 2017). Basically, scale economies apply (i.e., increasing returns to scale) if a proportional increase in all output leads to a less than proportional increase in overall cost, that is, the value of SE is less than one. If the value is larger than one, the cost grows more than proportionally and hence diseconomies scale are present (i.e., decreasing returns to scale). Furthermore, the cost will increase as the same proportion when there are constant returns to scale, or, equivalently, the value of SE equals one.

Next, the scale efficiency for the sample banks is estimated. In the banking literature, numerous empirical studies ignore the actual estimation of scale efficiency and instead apply scale elasticity measures as an indicator of efficiency (e.g., Hadad et al., 2013;

Dong, Hamilton and Tippett, 2014; Badunenko and Kumbhakar, 2017; and Köster and Pelster, 2017). These papers assume the measures of scale efficiency and scale elasticity are effectively synonymous: the derivation of one offers an accurate or approximate value for the other. Specifically, they consider that banks that yield constant returns to scale operate on the scale efficiency curve. That is, scale inefficiency estimates are considered to be linearly correlated with scale elasticity estimates – the values of scale inefficiency are equal to one minus elasticity values (Evanoff and Israilevich, 1995). From this viewpoint, statistically speaking, if scale elasticity takes the value of unity, the scale inefficiency estimate will be zero, implying 100% scale efficiency for those banks.

Here, we raise the doubts about representing scale efficiency just by elasticity measures – essentially these two concepts concern different things. A bank is deemed to be scale efficient when it is operating at optimal size for its particular input-output mix, and any size adjustments will cause the bank to be less efficient (Hou, Wang and Li, 2014). Scale inefficiency, thus, is measured as the change in outputs required to produce at the minimum efficient scale. Scale elasticity, however, is calculated on the basis of incremental changes in outputs. As suggested by Evanoff and Israilevich (1995), "*the inefficiency measure is typically associated with significantly larger output changes as one measures the difference in total or average cost at distinct output levels. The scale elasticity at the inefficient level of output suggests the initial path to the efficient output level. However, the initial path itself is inadequate to determine the efficient output. The cost savings realised by an incremental increase in output by a scale inefficient firm is irrelevant for measuring inefficiency since this is not the savings realised by producing at the efficient scale"* (page 1037).

In order to recognise the difference between these two cost concepts, also to identify how well the bank management maintains its average costs with respect to changes in its outputs, following Evanoff and Israilevich (1995), the cost term of scale inefficiency is also generated for sample Chinese banks. For the estimation, the proposed cost function (3.3) is generalised as below:

$$\ln TC_{it} = \left[\text{const} + \sum_k \beta_k \ln w_{kit} + {}^1\!/_2 \sum_k \sum_l \gamma_{kl} \ln w_{kit} \ln w_{lit} + \eta_1 T \right.$$
$$+ {}^1\!/_2\, \eta_2 T^2 + \sum_k \tau_k \ln w_{kit} T + \varphi_1 lnz_{it} + {}^1\!/_2\, \varphi_2 lnz_{it}^2$$
$$\left. + \sum_k \zeta_k \ln w_{kit} lnz_{it} \right] \tag{3.10}$$
$$+ \left[\alpha_i + {}^1\!/_2 \sum_i \sum_k \delta_{ik} \ln w_{kit} + \sum_n \theta_n T \right.$$
$$\left. + \sum_i \rho_i lnz_{it} \right] \ln Q_{it} + {}^1\!/_2\, [\sigma_{ij}]\, (\ln Q_{it})^2 + \varepsilon_{it}$$

where Q_{it} refers to the quantity of ith bank's outputs in year t. To simplify above equation, using coefficients a, b, c to represent the term in each set of brackets in equation (3.10):

$$\ln TC_{it} = \mathrm{a} + \mathrm{b} \ln Q + {}^1\!/_2\, c\, (\ln Q)^2 \tag{3.11}$$

Equation (3.11) reflects the underlying cost structure of the sample of Chinese banks. Next, we normalize Q around the level produced by scale-inefficient banks such that Q_{SI} = 1 and the output of the scale-efficient banks, Q_{SE}, is a multiple, A, of Q_{SI}.

Accordingly, for banks that are operating scale inefficiently:

$$\ln TC_{SI} = \mathrm{a} + \mathrm{b} \ln Q_{SI} + {}^1\!/_2\, c\, (\ln Q_{SI})^2 = a \tag{3.12}$$

and its scale elasticity is measured as

$$\varphi_{SI} = \partial \ln TC_{SI} \,/\, \partial \ln Q_{SI} = b \tag{3.13}$$

For banks that are operating on the efficient frontier:

$$\ln TC_{SE} = \mathrm{a} + \mathrm{b}\ln(A \times Q_{SI}) + {}^{1}\!/_{2}\, c\,(A \times \ln Q_{SI})^2 \tag{3.14}$$

and

$$\varphi_{SE} = \partial \ln TC_{SE} \,/\, \partial \ln\,(A \times \ln Q_{SI}) = 1 \tag{3.15}$$

since banks with scale elasticity measures that are non-significantly different from unity are considered to be scale-efficient banks. Taking the difference between equation (3.12) and (3.14), and with substitution of (3.13), the scale inefficiency can be estimated by

$$\mathrm{SI} = [A \times TC_{SI}/TC_{SE}] - 1 = A^{0.5(1-\varphi_{SI})} - 1 \tag{3.16}$$

which clearly shows that the assumption made in many empirical studies that scale inefficiency is linearly correlated with scale elasticity (as discussed on page 103) is incorrect. Scale inefficiency (SI) is not simply calculated as one minus elasticity estimates ($1-\varphi_{SI}$). This result invalidates the use of scale elasticity as a proxy for scale efficiency, and the role played by the output differential between inefficient and efficient banks is the primary reason for this inadequacy.

Moreover, SI can be solved in terms of the cost parameters only if the coefficient A is determined by the features of the proposed cost specification. That is, working out the value of A in terms of c, i.e., the second derivative of $\ln TC$, from (3.14) and (3.15), and then substituting A into equation (3.16), yields:

$$\mathrm{SI} = e^{(0.5/c)(1-\varphi_{SI})^2} - 1 \tag{3.17}$$

This shows that the scale inefficiency estimate is a function of first and second derivatives of the log cost function with regard to bank outputs. In a bid to have a clear view regarding the relationship between scale inefficiency and scale elasticity measures, we take equation (3.17) equivalent to $1-\varphi_{SI}$ to solve for the value of c.

When these two cost terms are equal, c will be

$$\mathrm{c}* = {}^{1}\!/_{2}\, (\varphi_{SI} * -1)^2 / \ln(2 - \varphi_{SI} *) \tag{3.18}$$

Accordingly, when $\varphi_{SI} *$ is significantly less than unity, which means investigated banks are enjoying substantial increasing returns through scale economies, larger φ_{SI} values will produce SI values smaller than $1-\varphi_{SI}$. Conversely, SI estimates are higher than $1-\varphi_{SI}$ if scale elasticity estimates are smaller than $\varphi_{SI} *$. A similar hypothesis can be made for $\varphi_{SI} *$ with values that are greater than unity. For the estimation of φ, when obtained estimates equal unity, this does not necessarily mean that SI will be equal to 0. Again, this shows the differences between the measurement of scale inefficiency and scale elasticity. On the basis of equation (3.13), these differences not only exist for their measures, but also appear in the estimation of standard errors. That is, equation (3.13) indicates that the statistical difference of φ from the level of unity solely depends on the standard error of coefficient b, while the standard error for SI is based on the covariance and variance of the estimates for coefficients b, c:

$$\begin{aligned} \mathrm{var}\ (\mathrm{SI}) = {} & (\partial \mathrm{SI}/\, \partial \mathrm{b})^2 \times var\ (b) + (\partial \mathrm{SI}/\, \partial \mathrm{c})^2 \times var\ (c) \\ & + (\partial \mathrm{SI}/\, \partial \mathrm{b}) \times (\partial \mathrm{SI}/\, \partial \mathrm{c}) \times cov\ (b, c) \end{aligned} \tag{3.19}$$

Therefore, there is also notable difference for the test of statistical significance for φ and SI.

Having defined SI, we now move on to discuss the estimation of technological change. From the cost perspective, technological change can mean that the same output vector, y, could be achieved at lower cost mainly via the process of innovation, invention and/or diffusion, while holding inputs fixed (Tadesse, 2006). As analysed in section 3.2, examining the underlying technological progress of the Chinese banking system allows us to interpret the nature of evidenced scale economies in the industry and the recent trend of increasing sector size. Based on the above cost specification (3.3), technological change (THC) can be expressed as

$$THC = \frac{\partial lnTC}{\partial T} \tag{3.20}$$

where THC measures the changes in bank costs resulting from changes in technology across the observation period. The same bundle of outputs can be produced at lower expenditure if the value of THC is negative (see, DeYoung, Kowalik and Reidhill, 2013). Nevertheless, our research multiplies THC by -1 for a more intuitive interpretation so that a positive value indicates technical progress for sample banks.

Moreover, THC may be scale-biased in the sense that it could change the quantity of y over which given scale economies can be generated, and thereby lead to a change in the cost-minimising efficient bank size. By further decomposing THC, a measure of technological scale bias (TSB) is:

$$TSB = \frac{\partial lnTC}{\partial lny \partial T} \tag{3.21}$$

If TSB is negative, then, as a result of THC, production at the previously optimal scale is no longer cost efficient – the bank needs to expand its asset size in order to minimise average costs (Simper, Dadoukis and Bryce, 2019). Again, TSB is multiplied by -1, so that a positive value indicates that the minimum efficient size of sample banks is increases as technological innovations are implemented.

3.4.2 Determinants of Economies of Scale

To examine the effects of diversification in the business model and risk-taking features on the realisation of economies of scale in Chinese banking, following Arellano and Bond (1991) and Athanasoglou, Brissimis and Delis (2008), we use a dynamic panel data regression[81] of the following form:

$$y_{it} = const + \alpha y_{it-1} + \beta x_{it} + \varepsilon_{it} \quad |\alpha| < 1, i = 1, \dots, N, t \dots, T$$
$$\varepsilon_{it} = u_i + v_{it} \tag{3.22}$$

where y_{it-1} is the one-period lagged value of the dependent variable and α refers to the speed of adjustment to equilibrium. $const$ is a constant term, and x_{it} denotes the remaining included independent variables (all variables are specified in equation 3.23). The ε_{it} term consists of two components – with v_{it} being the error term and u_i referring to unobserved panel effects.

On the basis of equation (3.22), the following dynamic baseline regression is proposed:

$$SE_{it} = const + \alpha SE_{it-1} + \beta_1 SEC_{it} + \beta_2 SFTF_{it} + \beta_3 LR_{it} + \beta_4 LRsq_{it} + \beta_5 LLP_{it} + \beta_6 T1_{it} + v_{it} \tag{3.23}$$

where SE_{it} denotes scale economies for bank i in year t, measured through equation (3.9), in which higher values suggest lower levels of scale economies exploited by banks. SE_{it-1} is the first-order lagged value of the dependent variable. It is included because it accounts for potential persistence concerns in the estimation, although this does complicate the estimation process. The coefficient on SE_{it-1}, α (a measure of the path dependency of SE_{it}), takes a value between 0 and 1 and reflects the persistence of any economies of scale. That is, theoretically, most economic relationships should be considered in a dynamic sense, and in view of the consideration that bank performance in previous time periods may influence future business decisions (e.g., Athanasoglou, Brissimis and Delis, 2008; Wooldridge, 2013;

[81] In the banking literature, panel data (cross-section time-series data) has been extensively applied in empirical studies (see, for example, Berger and Mester, 2003; Pasiouras and Kosmidou, 2007; Arif and Anees, 2012; Cummings and Durrani, 2016; Partovi and Matousek, 2019). The benefits of proposing a panel data model are the following: (i) more informative as it allows the inclusion of variables at different levels of analysis; (ii) alleviates collinearity issues; (iii) allows for considerations of adjustment dynamics; (iv) accounts for individual heterogeneity by allowing the panel dimension of the dataset to be treated as heterogeneous; and (v) helps reduce the magnitude of omitted-variable bias since the within estimator eliminates unobserved heterogeneity and its associated omitted-variable bias (Torres-Reyna, 2014).

Chronopoulos et al., 2015; and Badunenko and Kumbhakar, 2017), a lagged dependent term SE_{it-1} is included (as a dynamic component) in the above baseline model[82]. With respect to the remaining bank-specific determinants proposed in equation (3.23), the motivation for the selection of these determinants is based on Beccalli, Anolli and Borello (2015)[83]. Specifically, SEC_{it} is the securities to total assets ratio for bank i at time t. This ratio is deemed to be an indicator of diversification in the bank business model, whereby a higher ratio indicates a business model that focuses more on investment banking operations than on commercial banking activities. It is employed to examine whether the degree of scale economies achieved is affected by variations in the bank business model. $SFTF_{it}$, short-term funding to total funding ratio for bank i in year t, represents banks' funding strategy, and is used to test whether the exploitation of scale economies in banking can benefit from the utilisation of short-term wholesale funds.

The influence of risk-taking features on the realisation of scale economies is investigated via consideration of LR_{it} and LLP_{it}. LR_{it} is the liquidity ratio for bank i at time t, proxied by the ratio of liquid assets to deposits and short-term funding, measuring the capacity of a bank to repay its debt without raising external capital. This determinant is incorporated as an index of bank liquidity risk, with the hypothesis that higher values indicate lower probabilities of liquidity risk. Moreover, the squared term of the liquidity ratio for bank i at time t, $LRsq_{it}$, is also considered in equation (3.23), in order to test for the presence of a non-linear correlation between bank scale economies and liquidity. The credit risk is proxied by LLP_{it} – the loan loss provision ratio for bank i in year t – measured as the ratio of gross loans to loan loss provision (the higher the ratio, the greater the credit risk).

The effects of capital strength are tested by examining the coefficient on $T1_{it}$, where

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[82] We estimate equation (3.23) with different subsets of SE lags, and the first order is selected based on Akaike's/Schwarz's Bayesian information criteria, as it yields the smallest test value.

[83] Building on Bertay, Demirgüc-Kunt and Huizinga (2013), Beccalli, Anolli and Borello (2015) extend their examination of the chosen set of bank-level determinants (leverage, concentration in lending, share of bank income from non-interest sources, dependence on deposit funding, use of wholesale funding, bank probability of default) from size (systemic size and asset size) to scale economies in banking.

$T1_{it}$ denotes Tier 1 regulatory capital ratio for bank i in year t (measured as Tier 1 capital minus regulatory deduction as a percentage of bank risk-weighted assets). Finally, v_{it} is the equation error term. Then, with an eye to the significance of 'too big to fail', the TBTF dummy variable and its interaction term with $T1_{it}$ is added into baseline regression (3.23). Accordingly, the extended model can be specified as:

$$\begin{aligned} SE_{it} = const + \alpha SE_{it-1} + \beta_1 SEC_{it} + \beta_2 SFTF_{it} + \beta_3 LR_{it} + \beta_4 LRsq_{it} \\ + \beta_5 LLP_{it} + \beta_6 T1_{it} + \beta_7 TBTF_i + \beta_8 T1_{it} * TBTF_i + v_{it} \end{aligned} \quad (3.24)$$

where $TBTF_i$ is a dummy variable that takes the value of 1 for the 15 Chinese TBTF banks[84] (as identified in section 3.3.2), or 0 otherwise. See Table 3.7 for an overview of all the variables included in our bank scale economies regressions (equations 3.23 and 3.24).

Here, our focus is to examine whether the TBTF status of these 15 banks increases the level of scale economies attained by them. Correspondingly, a new dummy variable, $TBTF_i$, is generated and included into above regression (3.24) for estimation. In this way, our sample (135 Chinese commercial banks[85]) is partitioned into two groups: 15 TBTF banks and 120 non-TBTF banks. Then, the question of whether TBTF banks are able to realise a higher extent of cost economies than non-TBTF banks is investigated. As mentioned, such an examination offers empirical evidence for current regulatory discussions of downsizing in banking. The rationale for us to use the $TBTF_i$ dummy variable instead of the yearly systemic importance scores/rankings in regression (3.24) to examine the significance of 'too big to fail' is because the information of systemic importance scores/rankings is only available for the 15 TBTF banks and using these scores/rankings for estimation cannot meet our aim of comparing the capacity of TBTF banks relative to non-TBTF banks in attaining cost economies.

[84] To recap, based on the PBOC's stress testing bank list, those 15 listed Chinese banks are the so-called 'too big to fail' banks in the Chinese banking market and are potential D-SIBs in nature. They are the Big Four, Bank of Communications, China CITIC Bank, China Everbright Bank, China Merchants Bank, China Minsheng Banking Corporation, China Zheshang Bank, Hua Xia Bank, Industrial Bank, Ping An Bank, Postal Savings Bank of China, and Shanghai Pudong Development Bank.

[85] See section 3.4.3 on pages 118-119 for a detailed interpretation of our sample collection.

That is, when the yearly systemic importance scores/rankings rather than the $TBTF_i$ dummy variable are used in estimation, our focus will change from examining whether TBTF banks can achieve more scale economies than non-TBTF banks to evaluating the effects of bank systemic importance on scale economies. Accordingly, the choice to include the yearly systemic importance scores/rankings instead of the $TBTF_i$ dummy variable as a determinant of scale economies in estimation defeats the purpose of our analysis. Besides, as specified in above Tables 3.5 and 3.6 on pages 96-97, the data of yearly systemic importance scores/rankings is only available for the 15 TBTF banks. Regarding the 120 non-TBTF sample banks, they will display missing values for the yearly systemic importance scores/rankings variable during estimation, and this can lead to a biased estimate of the coefficient of this variable in the regression. Moreover, by generating the $TBTF_i$ dummy variable, its interaction term with $T1_{it}$ then can be considered in estimation, enriching our analysis by offering information on whether capital strength affects the realisation of scale economies of TBTF banks and non-TBTF banks differently.

Looking at these two groups of banks, section 3.3.2 evaluates the systemic importance of the 15 Chinese TBTF banks. To briefly recap, 6 state-owned commercial banks and 9 joint-stock commercial banks are recognised as TBTF banks in our study, whereby the 6 state-owned banks dominate the systemic importance at a high level (see Table 3.5). With respect to the 120 non-TBTF banks in our sample, they are made up of 1 joint-stock commercial bank, 66 city commercial banks, 26 rural commercial banks as well as 27 foreign commercial banks. Interestingly, one joint-stock bank, China Bohai Bank, cannot demonstrate itself as potential systemically important and hence is not deemed to be a domestic systemically important bank in our sample. This is mainly due to its relatively small asset size compared with the asset scale of the 9 TBTF joint-stock banks and its limited network of contractual obligations with other financial institutions (Chen et al., 2014).

That is, China Bohai Bank, a newly established joint-stock bank in 2005, is the smallest nationwide commercial bank. In 2015, its asset size was CNY421,352 million, much smaller (nearly 38% less) than the size of the smallest joint-stock bank on the TBTF list (namely China Zheshang Bank). Besides, China Bohai Bank exhibits a rather limited extent of systemic interconnectedness, considering its small scale of exposures to intra-financial system assets and liabilities. For example, the total amount of loans and advances to banks of China Zheshang Bank was CNY52,261 million in 2015, this figure is about three times bigger than that of China Bohai Bank (CNY17,899 million)[86]. In consequence, China Bohai Bank is not on the TBTF list. Concerning the remaining city commercial banks, rural commercial banks and foreign commercial banks in our sample, they tend to be recipients of systemic risk and, in the case of unexpected shocks, can be severely affected by the spill-over effects that arise from the distress of banks that are TBTF. In conclusion, to examine the significance of TBTF, the differences in performance between TBTF banks and non-TBTF banks in achieving scale economies are inspected. Its findings shed the light on the policy choice for banking authorities.

One issue worth noting is that the presence of the lagged term SE_{it-1} complicates the estimation of equations (3.23) and (3.24), as it gives rise to the limitation of that panel fixed effects are always correlated with the lagged dependent variable. Indeed, one major problem is that SE_{it-1} is correlated with the error term, which breaches the assumption of strict exogeneity and thereby results in biased and inconsistent estimators (Simper, Dadoukis and Bryce, 2019). In this circumstance, the system generalised method of moments (GMM) approach is employed by us for the estimation of dynamic panel regressions (3.23) and (3.24). GMM deals with possible panel heteroscedasticity, autocorrelation and endogeneity issues, and allows the inclusion of exogenous regressors and instrumental variables (Bryce et al., 2015).

The following approach is taken here to overcome the above concern. By way of example, consider the generalised form of dynamic panel data regression (3.22). If the first difference of the regression equation is used, this erases the individual effects (thereby eliminating a potential source of ‘omitted variable’ bias in the estimation) and allows for the potential inclusion of endogenous explanatory variables[87]. This can be

[86] Data reported by Orbis Bank Focus Database.

[87] First differencing equation (3.22) allows the issue to turn into the straightforward instrumental variables issue. This is the estimator developed by Anderson and Hsiao (1981) where instrumental

specified as

$$\Delta y_{it} = \alpha \Delta y_{it-1} + \beta \Delta x_{it} + \Delta \varepsilon_{it} \tag{3.25}$$

Arellano and Bond (1991) advise the use of the GMM technique because it takes advantages of all the available moment conditions from which instrumental variables can be drawn. Under the GMM procedure, the set of available instrumental variables utilised in the estimation of equation (3.25) is derived from the following moment conditions:

$$\mathrm{E}(x_{it-s}\Delta\varepsilon_{it}) = \mathrm{E}(y_{it-s}\Delta\varepsilon_{it}) = 0 \ldots s > j \tag{3.26}$$

Moreover, Blundell and Bond (1998) argue that the standard Arellano and Bond (1991) estimator for equation (3.25) has poor finite sample properties (in terms of bias and inaccuracy) in two cases. One is when the variance of u_i is larger than the variance of v_{it}, while the other is when the series are highly persistent. In both circumstances, weak instruments appear to be a problem since lagged levels are only weakly correlated with subsequent first differences, which in turn leads to imprecise estimates. To accommodate this limitation, both lagged differences and levels can be employed if lagged levels are perceived to be weak instruments (particularly when the variables are close to a random walk). That is, Arellano and Bover (1995) and Blundell and Bond (1998) propose the system of equations shown here as equation (3.27), which consists of the equation in differences and in levels, in a stacked form:

$$\begin{bmatrix} y_{it} \\ \Delta y_{it} \end{bmatrix} = const + \alpha \begin{bmatrix} y_{it-1} \\ \Delta y_{it-1} \end{bmatrix} + \beta \begin{bmatrix} x_{it} \\ \Delta x_{it} \end{bmatrix} + \varepsilon_{it} \tag{3.27}$$

As mentioned, on the basis of the standard first-differenced GMM estimator, Arellano and Bover (1995) and Blundell and Bond (1998) put forward an additional assumption that the first differences of instrumental variables are not correlated with the panel fixed effects. In this sense, the adoption of additional instruments becomes a valid

variables can be constructed in the form of lagged levels or lagged differences.

choice, thereby remarkably enhancing efficiency by building a system of two equations (Bryce et al., 2015). Equation (3.27) can be estimated as a system and is the generalised form of our proposed system GMM function for regressions (3.23 and 3.24). Accordingly, in GMM estimation, concerning our model specifications (3.23 and 3.24), the lagged dependent variable SE_{it-1} is treated as a predetermined regressor, where the standard treatment (Roodman, 2009a) is followed, instrumentalising it with its own first lag. Considering the remaining bank-level determinants, related banking studies do not provide a consensus on whether or not these regressors are exogenous or endogenous (Simper, Dadoukis and Bryce, 2019). However, the possibility of endogeneity may emerge because of the reverse causality between dependent variables and bank-specific regressors.

To illustrate, banks with superior capital strength are likely to enjoy lower levels of scale economies as the tougher Basel III capital requirement appears to reduce cost economies in banking (Beccalli, Anolli and Borello, 2015). This correlation also may flow in the opposite direction. For instance, banks that produce greater economies of scale are normally inclined to expand their asset size, but regulatory requirements for capital reserves will rise with the increase in bank size. This is an example of reverse causality between bank scale economies and its determinants[88]. In general, in the case of system GMM, potential endogeneity issues are covered by utilising valid instrumental variables (IVs), as these variables are considered to be solely related to potential endogenous explanatory variables and not correlated with the function error term (Tan and Anchor, 2017).

The IV regression is integral to the GMM estimation, although several post-estimation tests need to be performed. Specifically, the number of IVs utilised, the validity of the instruments as well as potential serial correlations in the model specification require our attention. As for the concerns related to the number of IVs utilised, the banking

[88] Beccalli, Anolli and Borello (2015) also perform the Granger causality tests to verify the existence of a unidirectional causality running from liquidity ratio, Tier 1 capital and systemic risk to scale economies.

literature does not provide a conclusive rule as to the optimal number of IVs for GMM estimation. Given the consensus that the utilisation of redundant IVs (instrument proliferation) may lead to a downward bias for GMM estimates, Hansen, Hausman and Newey (2008) and Roodman (2009b) suggest that the number of IVs that can be incorporated is restricted by the number of groups in the equation. We follow their proposal to argue that the number of cross-sectional units limits the number of IVs that can be included and determine that the number of IVs selected should be close to, yet smaller than, the number of groups present in our sample dataset.

This target can be achieved with the help of 'collapse'-style instruments in the system GMM. The instruments, in the case of 'collapse' technique, produce only one for each variable and lag distance, and the number of IVs depends on the available lag count and time period count. It should be noted that internal instruments that are available within the panel itself are adopted as IVs, as it is difficult to identify a group of valid external instruments for our study in which all bank-specific variables (excluding the autoregressive component) may be endogenous. It follows that another critical issue concerns the validity of instruments used – IVs should be exogenous (only correlated with possible endogenous regressors and not correlated with the error term) and the correlation with potentially endogenous variables should be strong.

Following Roodman (2009a), both the validity of the subsets of GMM-style instruments and the joint validity of all IVs are examined. On the one hand, the popular Hansen J-statistic is calculated, with the chi-squared distribution to test the whole set of over-identifying restrictions, under the null hypothesis of all instruments being valid IVs. Failure to reject the null hypothesis implies that no correlations exist between the IVs included and the error term in the model specification. On the other hand, the difference in the Hansen test under the null hypothesis of validity of the entire instrument group is calculated to assess the validity of the subsets of utilised instruments. That is, the test evaluates the difference between two Hansen statistics. One is the excluded group (unrestricted) estimation, that is, without a subgroup of suspect instruments, and the other is the estimation with the larger group of instruments. Baum, Schaffer and Stillman (2003) specify that the difference between the two obtained statistics has a degree of freedom equivalent to the number of instruments.

Failure to reject the null hypothesis shows that the specified explanatory variables are indeed endogenous and confirms that the specified subsets of IVs are valid instruments. Then the model specification needs to satisfy the assumption of no autocorrelation in error terms. A standard Arellano-Bond test for AR (1) and AR (2) can be performed to check this by examining that the differenced error components are in fact not second-order serially correlated. Furthermore, Windmeijer's (2005) finite sample correction is applied in order to deal with potential downward bias in estimators. When all the above post-estimation diagnostics are satisfied, our specifications are free from the main bias and, thus, the estimators produced provide a basis for the identification of the determinants of banks' scale economies.

Table 3.7: Variables incorporated in the proposed model specifications (3.23) and (3.24).

Incorporated variables	Notation	Measurement	Testing effects
Dependent variables:			
Scale economies	SE	Estimated by equation (3.9)	
Bank specific variables:			
Securities to total assets ratio	SEC	$Total\ securities/total\ assets$	Asset diversification
Short-term funding to total funding ratio	$SFTF$	$(Interbank\ borrowings + certificates\ of\ deposit + short\ term\ bonds)/total\ funding$	Funding strategy
Liquidity ratio	LR	$Liquid\ assets/deposits\ and\ short\ term\ funding$	Liquidity risk
Loan loss provision ratio	LLP	$Loan\ loss\ provisions/gross\ loans$	Credit risk
Tier 1 regulatory capital ratio	$T1$	$\frac{Tier\ 1\ capital - Regulatory\ deductions}{Risk\ weighted\ assets} * 100\%$	Capital strength
Too big to fail	$TBTF$	A dummy variable that takes the value of 1 for the 15 Chinese TBTF banks, or 0 otherwise.	TBTF status

For the list of 15 Chinese TBTF banks, see footnote 84.

Source: Author's own calculations

3.4.3 Data and Variables Used in the Study

This study utilises annual accounting data, eligible and regulatory capital information for 135 Chinese commercial banks over the sample period of 2005 to 2015[89]. Among these banks, 6 are state-owned commercial banks[90] and 10 are joint-stock commercial banks[91]. City and rural commercial banks collectively account for around 68% of the sample composition, of which there are 66 city commercial banks[92] and 26 rural commercial banks[93]. The remaining 27 banks are foreign commercial banks[94]. The

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89 Information was available for 184 commercial banks at the time of data collection; however, following the criteria proposed by Kosmidou (2008), only 135 commercial banks are included in the test sample for our estimation. To be incorporated into the sample, the following requirements had to be met. (i) All of the following observations with missing values, negative values or zero values are omitted: interest expense, operating expense, personnel expense, loans, other earning assets, loans and advances to banks, total assets, fixed assets, customer deposits, equity, non-performing loans and loan loss provision. (ii) All sample banks had to have at least one year of observations over 2005-2015 for the essential information and variables used in our empirical modelling.

90 They are: Agricultural Bank of China, Bank of China, Bank of Communications, China Construction Bank, Industrial & Commercial Bank of China, and Postal Savings Bank of China.

91 The 10 sample joint-stock commercial banks are: China Bohai Bank, China CITIC Bank, China Everbright Bank, China Merchants Bank, China Minsheng Banking, China Zheshang Bank, Hua Xia Bank, Industrial Bank, Ping An Bank, and Shanghai Pudong Development Bank.

92 These banks are: Bank of Langfang, Bank of Beijing, Bank of Cangzhou, Bank of Changsha, Bank of Chengdu, Bank of Chongqing, Bank of Dalian, Bank of Deyang, Bank of Dongguan, Bank of Fuxin, Bank of Guangzhou, Bank of Guilin, Bank of Guiyang, Bank of Hangzhou, Bank of Inner Mongolia, Bank of Jiangsu, Bank of Jilin, Bank of Jinhua, Bank of Jinhzou, Bank of Jiujiang, Bank of Lanzhou, Bank of Liaoyang, Bank of Luoyang, Bank of Nanjing, Bank of Ningbo, Bank of Qingdao, Bank of Rizhao, Bank of Shanghai, Bank of Shaoxing, Bank of Suzhou, Bank of Taizhou, Bank of Tianjin, Bank of Weifang, Bank of Wenzhou, Bank of XI'an, Bank of Yingkou, Bank of Zhengzhou, Baoshang Bank, China Guangfa Bank, China Resources Bank of Zhuhai, Chinese Mercantile Bank, Chongqing Three Gorges Bank, Dongying Bank, Fudian Bank, Fujian Haixia Bank, Guangdong Huaxing Bank, Guangdong Nanyue Bank, Guangxi Beibu Gulf Bank, Hankou Bank, Harbin Bank, Hubei Bank Corporation, Huishang Bank, Jiangxi Bank, Longjiang Bank Corporation, Nanchong City Commercial Bank, Ningbo Commerce Bank, Panzhihua City Commercial Bank, Qilu Bank, Qishang Bank, Shengjing Bank, Weihai City Commercial Bank, Xiamen Bank, Xiamen International Bank, Zhangjiakou City Commercial Bank, Zhejiang Chouzhou Commercial Bank, Zhejiang Mintai Commercial Bank.

93 These rural commercial banks include: Beijing Rural Commercial Bank, Changshu Rural Commercial Bank, Chengdu Rural Commercial Bank, Chongqing Rural Commercial Bank, Dongguan Rural Commercial Bank, Foshan Rural Commercial Bank, Guangdong Shunde Rural Commercial Bank, Guangzhou Rural Commercial Bank, Hangzhou United Rural Commercial Bank, Jiangsu Haian Rural Commercial Bank, Jiangsu Jiangnan Rural Commercial Bank, Jiangsu Jiangyin Rural Commercial Bank, Jiangsu Wujiang Rural Commercial Bank, Jiangsu Zijin Rural Commercial Bank, Jilin Jiutai Rural Commercial Bank, Nanhai Rural Commercial Bank, Ningbo Yinzhou Rural Cooperative Bank, Qingdao Rural Commercial Bank, Shanghai Rural Commercial Bank, Tianjin Binhai Rural Commercial Bank, Wuhan Rural Commercial Bank, Wuxi Rural Commercial Bank, Xiamen Rural Commercial Bank, Zhejiang Wenzhou Lucheng Rural Commercial Bank, Zhongshan Rural Commercial Bank, and Zhuhai Rural Commercial Bank.

94 The sample foreign commercial banks contain: Allied Commercial Bank, Australia and New Zealand

data were downloaded from the Orbis Bank Focus Database and the SNL financial Platform. These two international databases contain high-quality financial data (i.e., micro-level banking information) on worldwide banks and are widely employed by various leading financial institutions as well as supervisory authorities (e.g., central banks) for banking studies and policymaking (BIS, 2013). Spot checks were performed with financial statements of credit institutions to confirm the quality of the data and identify possible disparities. A panel dataset is constructed since it allows study of adjustment dynamics and deals with individual heterogeneity and collinearity issues (Fu and Heffernan, 2009).

Our research covers the period 2005 to 2015. There are two primary reasons for us to choose such this period. First, it seems useful to start the sample period in 2005, as that year was the deadline for Chinese banks to adopt a set of new banking standards due to China's accession to the WTO. Moreover, in that year China's largest Chinese banks 'went public' with great success and began to diversify by expanding their non-traditional fee-generating business.

Second, this time interval allows us to compare the performance of Chinese banks between the GFC period and post-crisis period in an effort to evaluate whether the crisis imposed 'too big to fail' considerations on Chinese banking. That is, the study explores whether large Chinese banks enjoy significant cost advantages due to their size strength and whether the cost efficiencies arise from scale economies or 'too big to fail' subsidies. In addition, we also include the period of the phasing-in of the Basel II & III new capital requirements in China. In turn, the study's findings can be utilised by these banks to strengthen their current weak condition.

Bank (China), BNP Paribas (China), Bank of East Asia (China), Bank of Montreal (China), Bank of Tokyo Mitsubishi UFJ (China), Citibank (China), Credit Agricole CIB (China), DBS BANK (China), Dah Sing Bank (China), Fubon Bank (China), HSBC Bank (China), Hana Bank (China), Hang Seng Bank (China), Industrial Bank of Korea (China), JP Morgan Chase Bank (China), Metropolitan Bank (China), Mizuho Bank (China), Nanyang Commercial Bank (China), OCBC Bank (China), Royal Bank of Scotland (China), Shinhan Bank (China), Societe Generale (China), Standard Chartered Bank (China), Sumitomo Mitsui Bank(China), United Overseas Bank (China), and Wing Hang Bank (China).

3.4.3a Selection of Bank Inputs and Outputs

Next comes to the selection of inputs/outputs for our frontier estimation (function 3.3). The banking efficiency literature has featured a debate about the proper identification of inputs and outputs. The choice of appropriate inputs and outputs is a vital issue in building the model for bank efficiency research. This issue remains unresolved, but three modelling theories dominate – the production approach, the intermediation approach and the value-added approach (see, for example, Camanho and Dyson, 2005; Fiordelisi, Ibanez and Molyneux, 2011; Hughes and Mester, 2013; and Lin, Doan and Doong, 2016). Each modelling theory takes a distinct view regarding the role of banks, the financial service industry and its interconnectedness with the real economy.

With respect to the production approach, a bank is considered to be a financial service producer for customers – it operates transactions on deposits and processes products like loans for its account holders. This modelling methodology was devised by Benston and Smith (1976), who argue that "*we view the role of the financial intermediary as creating specialized financial commodities. These commodities are created whenever an intermediary finds that it can sell them for prices which are expected to cover all costs of their production, both direct costs and opportunity costs*" (page 215). Under this assumption, a bank is a financial intermediary that provides account holders with units of generalised purchasing power that can be transformed into financial services and products at a minimal transaction cost. This process, like any other production process, needs the input of various forms of labour and capital goods (Bryce et al., 2015).

This modelling theory suggests that banks economise on transactions costs. These costs are interpreted by Benston and Smith (1976) as costs of search, administration, transportation, monitoring, and evaluation, among others, and they point out that banks normally enjoy economies of scale, scope, and networks in these tasks. Accordingly, bank inputs normally contain the physical and capital goods which are then required to perform transactions, such as the number of employees, the number of branch numbers and operational costs. For this approach, the output mix is the services that banks offer to their consumers and is best modelled using transaction flow data, which are rarely available (Sturm and Williams, 2008). Thus, the data on the stock of deposits and loans are usually used as proxies for bank outputs, as those data reflect the level of services provided. That is, the total value of deposits, total value of loans and the number of general service transactions are commonly included bank outputs in the production approach.

While the production modelling methodology emphasises operational activities, the intermediation approach regards banks as financial intermediaries between liability holders and those who receive bank funds (Nguyen, 2018). More specifically, banks are institutions that perform intermediation services through the collecting of deposits and other liabilities from surplus units and then lending these financial assets to deficit units in the form of various types of interest-bearing assets (e.g., loans and securities). This approach was first proposed by Sealey and Lindley (1977), who state:

> "*As a result of the preceeding analysis the production process of the financial firm, from the firm's viewpoint, is a multistage production process involving intermediate outputs, where loanable funds, borrowed from depositors and serviced by the firm with the use of capital, labour and material inputs, are used in the production of earning assets… Eventually, the intermediate outputs culminate in the final economic output of the firm, i.e., earning assets. The output of the financial firm is, therefore, produced with capital, labour, material, and loanable fund inputs where loanable funds are "produced" through other production operations of the financial firm*" (page 1254).

Accordingly, this modelling theory pays attention to banks' intermediation activities, hence, the financial services that are offered to the investors such as loans seem to be the appropriate notion of bank outputs. Furthermore, the measures of outputs should be in physical units, in order to be employed by the cost or production function (Blau, Brough and Griffith, 2017). Some commonly adopted bank output variables are the price of loans and deposits, while fixed assets, loanable funds and labour are frequently chosen bank input variables (see, for instance, Camanho and Dyson, 2005, Bryce et al., 2015 and Rahman et al., 2018).

In addition to the above two approaches, the value-added approach is a more recent modelling methodology for the cost estimation of banks. This approach was first developed by Berger, Hanweck and Humphrey (1987) and then extended by Drake, Hall and Simper (2006). It identifies asset and liability accounts as balance sheet categories that have bank output features, instead of deciding inputs from outputs in a mutually exclusive way. That is, those bank deposits and loans accounts are deemed to be outputs, as they contribute to the great majority of bank value added. The underlying criterion is that "*banking functions which are associated with a substantial labour or physical capital expenditure to produce a (noninterest) flow of banking services are identified as the important outputs*" (Berger and Humphrey, 1991, page 126). Moreover, physical capital expenditures, purchased funds and labour are normally incorporated as input variables. It is worth noting that deposits may also be classified as having input features because these accounts offer a great portion of the supply of investable funds in creating loan outputs. Nowadays, this approach has received increasing attention in the banking literature, and a substantial number of studies have adopted this theory (e.g., Pasiouras, Tanna and Zopounidis, 2009; Goddard, Molyneux and Williams, 2014; Quaranta, Raffoni and Visani, 2018).

Among these three approaches, the production and intermediation approach are the two most widely recognised in determining input and output prices of the cost function of a bank. See, for example, the production approach employed in Ferrier and Lovell (1990), Fried, Knox Lovell and Eeckaut (1993), Sturm and Williams (2008) and Doan, Lin and Doong (2018); and the intermediation approach utilised in Drake, Hall and Simper (2006), Hadad et al. (2012) and Bryce et al. (2015). The major difference between these two methodologies is that they recognise different roles for banks – while the former views banks as production units, the latter views banks as assets transformers whose task is transforming money[95] borrowed from depositors into money lent to

[95] Sealey and Lindley (1977) argue that "*The transformation process for a financial firm involves the borrowing of funds from surplus spending units and lending those funds to deficit spending units, i.e., financial intermediation. The depository financial firm's output in a technical sense is thus a set of financial services to the firm's depositors (creditors) and borrowers. These services may be categorized into (1) administration of the payments mechanism for demand deposit customers in the case of a commercial bank, (2) intermediation services to depositors and borrowers in the case of a commercial bank or other depository institution, and (3) other services such as trust department activities, portfolio*

borrowers.

Bryce et al. (2015) suggest that the intermediation approach estimates banks' cost structure more precisely than the other two approaches, given that interest expense is considered as an important bank input, while the production approach excludes this variable as it solely focuses on banks' operating processes. Moreover, another rationale for us following the intermediation approach for the Chinese banking cost scale economies and efficiency estimation lies in the legal definition of a bank in China: "*Bank means a type of credit institution which may conduct all banking operations*…including…*taking in deposits from the general public, granting short-term, medium-term and long-term credits, issuing financial bonds, providing safe deposit box services, and acting as an agent for the receipt and payment of money and acting as an insurance agent*" (Law of the People's Republic of China on Commercial Banks, 2003). Hence, the intermediation approach is preferred in our study[96]. Following this assumption, personnel expenses, total interest expenses and other operating expenses are the chosen inputs, while gross loans, other earning assets and loans and advances to banks are the selected outputs for our cost function.

3.4.3b Selection of Risk Control Variables

The incorporation of risk proxies into a cost function has been done in several recent banking studies. For example, Delis, Iosifidi and Tsionas (2017) employ a framework that includes bank risk (measured as equity and loan loss provisions) within their frontier cost efficiency model in relation to US banks between 1976 to 2014. Their model assumes that bank risk is endogenously associated with bank efficiency, and the outcomes indicate that ignoring risk parameters in the model substantially biases their efficiency estimates and the ranking of banks according to their competitive advantage.

advisory services, etc" (page 1252). Indeed, the outputs and inputs of a bank must be clearly delineated before a model of production and cost can be developed for this bank.

[96] This approach provides us with insights into how costs vary alongside the increases in outputs and offers light on how outputs and costs will react to the current trend for mergers in the Chinese banking sector and the rising competition that emanates from outside the banking industry.

Moreover, a significant negative risk-efficiency nexus is found for sample banks, with causality running both ways. Similar arguments about the importance of adding risk variables are made by Wheelock and Wilson (2012) and Bryce et al. (2015).

Wheelock and Wilson (2012) include equity risk in their proposed cost specification to estimate ray-scale and expansion-path scale economies for US banks across the period 1984 to 2006. Their findings demonstrate that risk variables indeed affect the levels of scale economies estimated for sample banks. They point out that taking risk characteristics into account is necessary since estimating bank scale economies and efficiency is made more complex by risk taking. Greater diversification resulting from larger scale generates scale economies for banks but also incentivises them to take on more risks. When this extra risk-taking adds to cost, it can obscure underlying scale economies and engender misleading econometric estimates of them.[97]

Bryce et al. (2015) examine the cost and X-efficiency of the Vietnam banking sector over the period 2006 to 2012. Bank equity and loan loss provisions are incorporated as risk management variables to account for the risk characteristics of sample banks in their paper. Their empirical results suggest that risk factors indeed have a marked impact on the cost efficiency scores of Vietnam banks, since well capitalised banks generally get higher efficiency scores than banks with insufficient capital reserves.

Our analysis contributes to the Chinese banking literature because it is one of the few empirical studies to capture banking risk: bank equity, loan loss provision (LLP) and non-performing loans (NPL) are the three risk control variables selected to reflect the risk profiles of sample banks in the cost equation (3.3). These three risk variables are chosen because they give the best picture of the risk behaviours of Chinese banking sector over the sample period. Bank equity mirrors the regulatory cost imposed by Basel III regulations; loan loss provision indicates the risk-taking of sample banks

[97] Hughes and Mester (2013) also make this point. As suggested by Hughes and Mester (2013), "*estimating scale economies is made more complex by risk-taking… Systematic differences in risk among banks can significantly alter how their cost varies with output and consequently engender misleading econometric estimates of their scale economies when endogenous risk-taking is not taken into account in modelling and estimating bank cost*" (page 559).

engaging in shadow banking operations (see section 2.7); and Chinese banks have historically been burdened by a large number of non-performing loans (see section 2.5). All the variables for the cost specification (3.3) are presented in Table 3.8. It should be noted that all data are deflated by the GDP deflator (year 2005 is the base year) to eliminate the impact of inflation on estimations.

Table 3.8: Summary of variables selected for equation (3.3).

Variables	Measurements
Inputs (X):	
X1	Personnel expenses
X2	Total interest expenses
X3	Other operating expenses
Outputs (Y):	
Y1	Gross loans
Y2	Other earning assets
Y3	Loans and advances to banks
Input Prices:	
P1	X1 / fixed assets
P2	X2 / average customer deposits
P3	X3 / fixed assets
Risk Variables:	
Z1	Equity
Z2	Loan impairment charge (loan loss provisions)
Z3	Total impaired loans (non-performing loans)
Cost variable:	
Total Costs	X1 + X2 + X3

Source: Author's own calculations

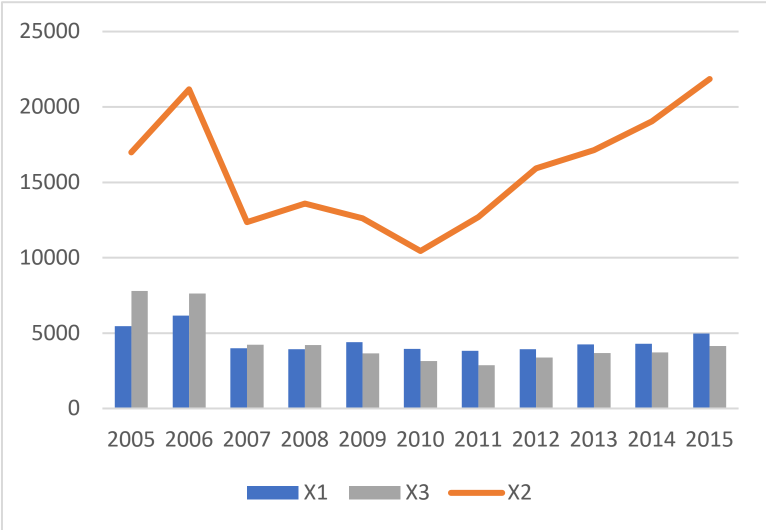
3.4.4 Summary Statistics

The descriptive statistics of all selected variables for the cost function (3.3) are presented in Table 3.9. With respect to the inputs, the balance of total interest expense is considerably higher than those for other operating expense and personnel expense (see Figure 3.1). As stated, the Chinese banking industry seems remain immature and underdeveloped compared with its main counterparts, and thus offers limited choices of financial instruments and restricted investment markets. In this environment, Chinese banks tend to rely on traditional banking services (deposit-taking) to earn their profits. This could be a main reason for the significant difference between the balance of total interest expense and other operating expense. Before 2010, interest expenses saw a substantial decline for the sample banks, from CNY16,985.57 million to CNY10,443.69 million during 2005 to 2010. Then the liberalisation of interest rate accelerated the interest-bearing deposit costs for banks, reflected by an increase in the total interest expenses of sample banks from 2011 to 2015.

Moreover, it can be observed that changes in interest expenses and operating expenses follow the same pattern. They both increased in 2008 due to the costs stemming from the GFC, and there was another increase from 2011. Regarding the personnel expenses, its balance is relatively stable across the sample period.

As for outputs, Figure 3.2 shows that both gross loans and other earning assets increase overall from 2008. The downward trend of these two figures during 2005 to 2007 might be due to the ownership restructuring of Chinese banks. Not surprisingly, both values hit a floor in 2008 because of the GFC. In contrast, loans and advances to banks account are broadly stable over our study period. The recent improvements in bank outputs indicate that reforms of banks in China indeed resulted in a rapid expansion of the Chinese banking industry, especially in terms of credit growth. Overall, it shows current typical features of Chinese banks: huge asset size, higher profits associated with excessive costs, but also higher risks.

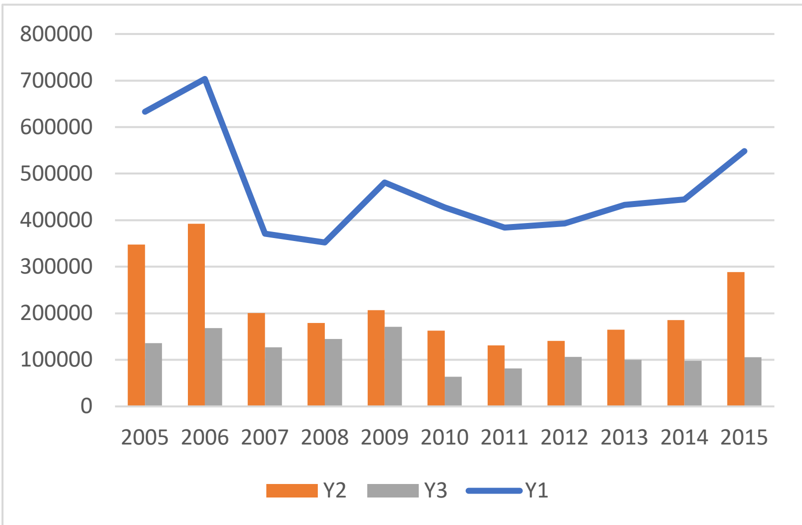
Figure 3.1: Mean of inputs (CNY million) for equation (3.3).



X1: personnel expenses, X2: total interest expenses, X3: other operating expenses.

Source: Author's own calculations

Figure 3.2: Mean of outputs (CNY million) for equation (3.3).

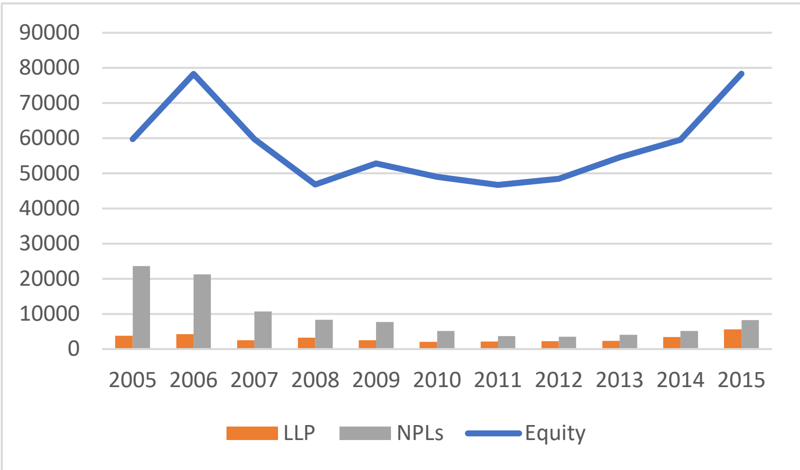


Y1: gross loans, Y2: other earning assets, Y3: loans and advances to banks

Source: Author's own calculations

Concerning the risk variables (equity, NPLs and LLP), Figure 3.3 shows that there was a roughly 31% increase in the level of capital of the sample banks between 2005 and 2006. Then there was a decrease among the sample banks due to the adverse impacts of the GFC during 2008, followed by a slight upward trend in 2009, which was a result of the capital injection of CNY4 trillion from the Chinese central bank, as an economic stimulus package. After the GFC, following the guidance of Basel III, the initiation of new capital requirements in Chinese banks began from 1 January 2013, which led to the introduction of a range of new capital rules to update previous relaxed domestic regulations compliant with recent rigorous international standards. Accordingly, a second wave of substantial capital improvements was witnessed by sample banks from 2013. More specifically, bank equity capital displayed an approximately 43% increase, from around CNY54583 million to CNY78342 million, over the period 2013 to 2015.

Figure 3.3: The evolution of equity, LLP and NPLs of sample banks (CNY million).



LLP: loan loss provision, NPLs: non-performing loans

Source: Author's own calculations

With the substantial increase in capital during 2005 and 2006, the situation of NPLs of Chinese banks was also enhanced: the outstanding stock of NPLs declined from about CNY23655 million in 2005 to around CNY21300 million in 2006. Then there was a marked drop in the balance of NPLs in 2007 – thanks to the transferral of the massive outstanding NPLs from the balance sheets of the Big Four to that of the newly established asset management companies (Wu, Song and Chai, 2018). This favourable decrease lasted six years, until NPLs increased again from 2011. Wang et al. (2014) and Zhang et al. (2016) argue that such growth was mainly attributed to a surge in the rate of default on bank loans of state-owned firms and increased bank exposures in the shadow banking market. Loan loss provision was relatively stable across the study period, with small variations in accordance with changes in the value of NPLs of sample banks since loan loss provision denotes an expense set aside to allow for default loans and loan payments (Simper, Dadoukis and Bryce, 2019).

Table 3.9: Descriptive statistics of variables selected for equation (3.3).

Variables	Mean	Std. Dev.	Min	Max
Inputs:				
X1	4289.16	11861.95	0.40	77887.48
X2	15909.01	38035.59	1.20	248256.51
X3	3847.29	9979.99	0.50	65071.00
Input prices:				
P1	1.69	3.13	0.09	41.74
P2	0.04	0.05	0.01	0.59
P3	1.44	2.76	0.09	42.05
Outputs:				
Y1	444529.53	1162924	71.18	8140871
Y2	193661	527030.67	0.17	3488041
Y3	108973.82	248665.95	17.55	1904833
Risk terms:				
Z1	54255.61	145720.1	41.9	1228293
Z2	2930.48	7843.26	0.14	63177.46
Z3	6436.08	18840.5	0.14	154417
Total costs:				
TC	24045.46	57463.73	2.1	370037.3

All values are expressed in millions of CNY.

where X1: personnel expenses, X2: total interest expenses, X3: other operating expenses, P1: X1 / fixed assets, P2: X2 / average customer deposits, P3: X3 / fixed assets, Y1: gross Loans, Y2: other earning assets, Y3: loans and advances to banks, Z1: equity, Z2: loan loss provision, Z3: non-performing loans, TC: X1+X2+X3.

Source: Author’s own calculations

Table 3.10 offers summary statistics of bank-level determinants included in our baseline dynamic panel regression (3.23). Regarding diversification in banks’ business models, the mean of securities to total assets ratio is 23.79% over the period 2005 to 2015, ranging from a minimum of 0.4% to a maximum of 68.08%, suggesting that our sample incorporates the largest Chinese banks, even if they are not necessarily investment banks. With respect to the bank characteristic of funding strategy, short-term funding to total funding ratio has an average value of 3.01%. Across the sample period, liquidity and credit risk vary widely among the sample banks. The highest liquidity ratio is reported by Metropolitan Bank (China), for 2011, an indication of its outstanding liquidity risk management in that year. Chongqing Rural Commercial Bank records the smallest loan loss provision, in 2010, whereas Bank of Suzhou reports the maximum, in 2015. On average, the Chinese banking industry seems to exhibit a fairly robust capital strength, considering the Tier 1 regulatory capital ratio generates a mean of 12.47% over the study period.

Table 3.10: Summary statistics (in %) of variables selected for equation (3.23).

Variables	Mean	Std. Dev.	Min	Max
SEC_{it}	23.79	11.5	0.4	68.08
$SFTF_{it}$	3.01	6.53	0	51.04
LR_{it}	27.02	14.74	2.64	134.99
LLP_{it}	15.78	12.57	0.06	101.28
$T1_{it}$	12.47	12.83	2.78	289.11

Where SEC_{it}: the securities to total assets ratio (%); $SFTF_{it}$: the short-term funding to total funding ratio (%); LR_{it}: the liquid assets to total customer deposits ratio (%); LLP_{it}: the loan loss provision to total loans ratio (%), and $T1_{it}$: the Tier 1 regulatory capital ratio (measured as the Tier 1 capital minus regulatory deductions as a percentage of bank risk-weighted assets).

Source: Author’s own calculations

In addition, the correlations among these included variables in equation (3.23) are examined and the results are shown in below Table 3.11. This corelation matrix indicates that there are no concerns regarding the multicollinearity issue as no pairs of included variables exhibit high correlations[98].

[98] The collinearity issue is examined by checking the correlation matrix. According to the rule of thumb, correlation coefficient values larger than 0.7 suggest there is cause for concern. It is evident that none of the variables included in our model present multicollinearity concerns.

Table 3.11: Correlation matrix of incorporated variables for equation (3.23).

	SE_{it}	SEC_{it}	$SFTF_{it}$	LR_{it}	LLP_{it}	$T1_{it}$
SE_{it}	1					
SEC_{it}	-0.398	1				
$SFTF_{it}$	0.241	-0.186	1			
LR_{it}	0.091	-0.192	0.099	1		
LLP_{it}	0.214	-0.022	0.035	-0.071	1	
$T1_{it}$	0.182	-0.164	0.067	0.489	-0.094	1

Where SE_{it}: scale economies estimates, SEC_{it}: the securities to total assets ratio (%); $SFTF_{it}$: the short-term funding to total funding ratio (%); LR_{it}: the liquid assets to total customer deposits ratio (%); LLP_{it}: the loan loss provision to total loans ratio (%), and $T1_{it}$: the Tier 1 regulatory capital ratio (measured as the Tier 1 capital minus regulatory deductions as a percentage of bank risk-weighted assets).

Source: Author's own calculations

3.5 Empirical Results of Bank Scale Estimation

3.5.1 Results of the Li test

As indicated in section 3.2, three risk factors are included separately or in different combinations in our scale economies and scale efficiency estimation (see Table 3.12). While Model 1 includes no risk variables, Models 2 to 4 consider the individual risk factors separately. Model 5 incorporates all three risk variables. Models 6 to 8 are the specifications when two risk factors are jointly (in different combinations) entered in the cost function (3.3). Scale economies and scale inefficiency are estimated respectively across each model specification through equations (3.9) and (3.17). The obtained estimates of scale economies across each model are presented in Table 7.1 and Table 7.2, while Table 7.3 and Table 7.4 (in Appendix A) exhibit the results of scale inefficiency estimates for Models 1 to 8.[99]

[99] Overall, Tables 7.1 to 7.4 (in Appendix A) show that each model specification yields different scale economies and scale inefficiency estimates. Without considering risk impacts, Model 1 finds evidence of slight diseconomies of scale for the full sample, suggesting that the Chinese banking system cannot gain cost savings by further expanding its size. Over the period 2005 to 2015, the efficiency performance of sample banks shows an overall improving trend, given the inefficiency value reduced from 5.87% to 2.54%, with a mean of 2.59%. Model 2, Model 3 and Model 7 document substantial diminishing returns to scale among Chinese banks throughout the sample period (with the exception of

Table 3.12: Models reflecting different bank input-output specifications.

Models	Input-output specifications
Model 1	3X+3Y
Model 2	3X+3Y+Equity
Model 3	3X+3Y+NPL
Model 4	3X+3Y+LLP
Model 5	3X+3Y+Equity+LLP+NPL
Model 6	3X+3Y+Equity+NPL
Model 7	3X+3Y+Equity+LLP
Model 8	3X+3Y+LLP+NPL

Where 3X is the three chosen bank inputs, i.e., personnel expenses, total interest expense and other operating expenses. 3Y means the three defined bank outputs, namely gross loans, other earning assets (excluding loans and advances to banks) and loans and advances to banks; NPL denotes non-performing loans, LLP is loan loss provisions.

Source: Author's own calculations

Then the Li test, proposed by Li (1996, 1999), is performed to examine the distributional equality of efficiency estimates across each model to determine which risk term should be considered when considering the best-fitted model specification with respect to the efficiency of the Chinese banking industry. The Li test compares the distributions of efficiency estimates from different models by estimating the corresponding densities and testing their equalities. In our case, it is performed utilising kernel-density estimators and bootstrap. Taking Model 1 and Model 2 as an example, let $\{SI_i^{M1}: i = 1, \dots, n\}$ denote the set of scale inefficiency estimates generated by Model 1 for sample banks, and $\{SI_i^{M2}: i = 1, \dots, n\}$ represent another set of scale inefficiency scores produced by Model 2 using the same sample.

Let f_{M1} be the probability density function for $\{SI_i^{M1}: i = 1, \dots, n\}$, with F_{M1} its corresponding distribution function. Similarly, the probability density function and

the years 2010 and 2011 in the estimation of Model 7). In addition, the mean values of inefficiency derived from these three models are the top three highest scale inefficiency estimates produced across the eight models – the highest values being 9.43% for Model 2, followed by 7.81% for Model 7 and 7.15% for Model 3. Similarly, under the estimation of Model 4, Model 5, Model 6 and Model 8, industry-wide diseconomies of scale are observed for Chinese banks over the period 2005 to 2015, whereas the mean level of scale inefficiency estimates generated from these four models (4–8) ranges from 1.93% to 6.13%.

distribution function of $\{SI_i^{M2}: i = 1, \dots, n\}$ are f_{M2} and F_{M2} respectively. Both $\{SI_i^{M1}: i = 1, \dots, n\}$ and $\{SI_i^{M2}: i = 1, \dots, n\}$ are assumed to be independently and identically distributed with densities. To test the distributional equality, the following hypothesis is developed:

$$H_0: \Pr\{f_{M1}(\mathrm{SI}) = f_{M2}(\mathrm{SI})\} = 1$$

Alternatively:

$$H_1: \Pr\{f_{M1}(\mathrm{SI}) \neq f_{M2}(\mathrm{SI})\}$$

A rejection of H_0 implies significantly differing distributions across Model 1 and Model 2. Repeating the above test to examine all eight model variations discussed in Table 3.12, a summary of the test results is outlined in Table 3.13. Figure 3.4 compares the actual distributions of scale inefficiency estimates derived from the different models for all possible permutations. The test results indicate that all permutations vary significantly across the models. Since incorporating a single risk variable, a pair of risk variables or all three risk variables yields significantly different inefficiency estimates, to capture a more comprehensive cost structure of Chinese banks, Model 5 (which includes all three risk factors) is considered to be the optimal model for the estimation of scale efficiency of the Chinese banking sector. Accordingly, in sections 3.5.2 to 3.5.4, only the estimation results of the best fitted model, Model 5, will be presented and analysed.

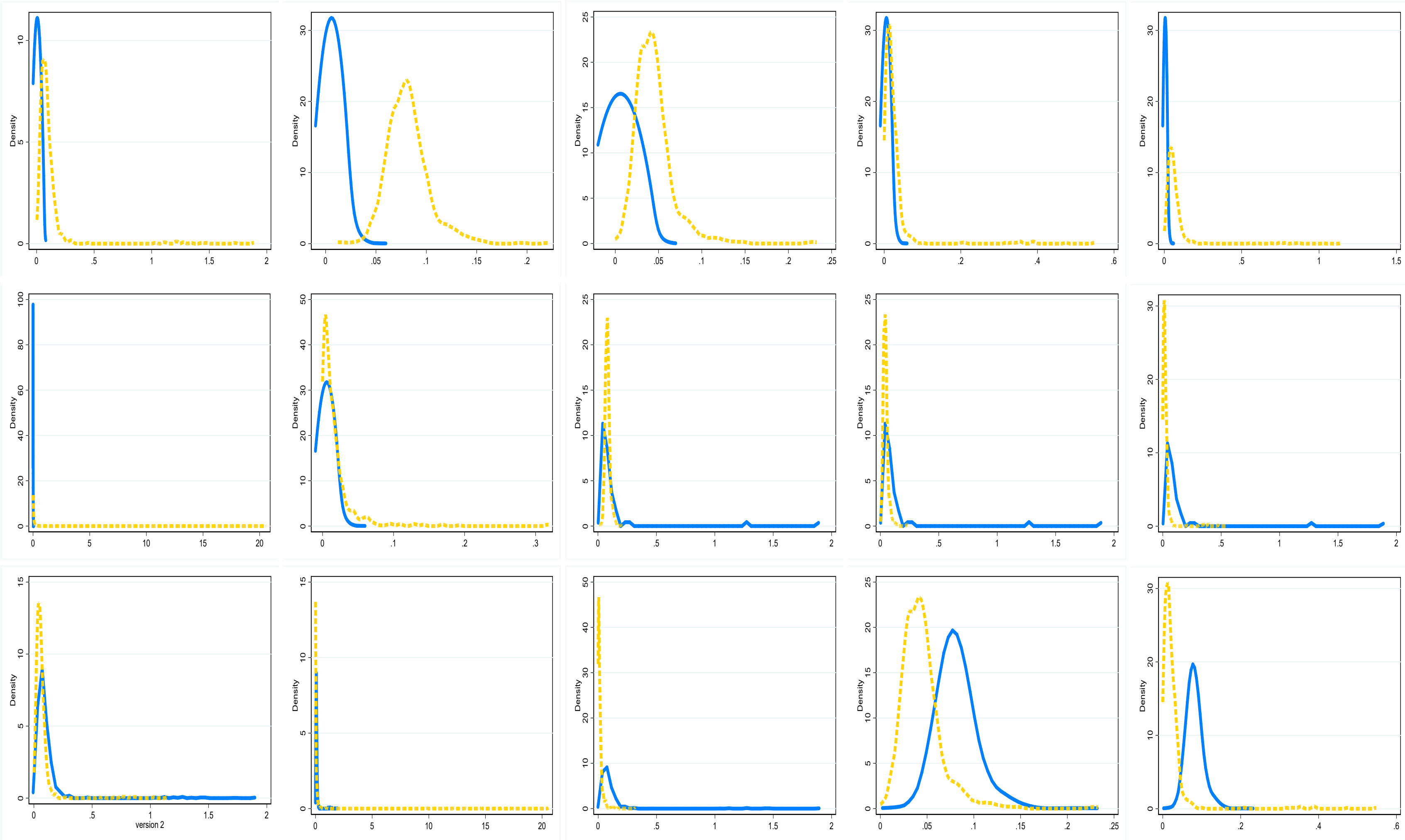
Table 3.13: Adapted Li test results.

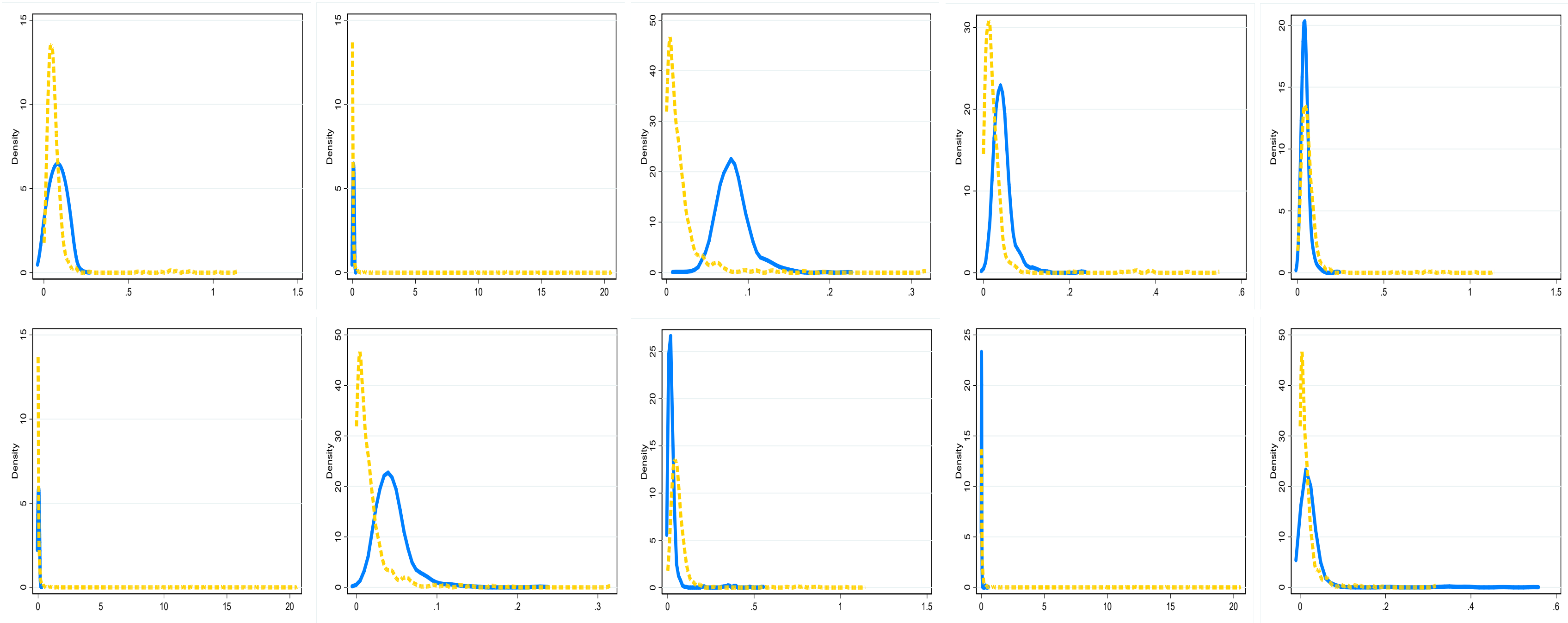
Models	Test Statistics	P value	Models	Test Statistics	P value
None vs EQ	280.6522	0.00	NPL vs EQ, NPL, LLP	356.1114	0.00
None vs NPL	313.7038	0.00	NPL vs EQ, NPL	117.1132	0.00
None vs LLP	296.2502	0.00	NPL vs EQ, LLP	292.3881	0.00
None vs EQ, NPL, LLP	110.5789	0.00	NPL vs NPL, LLP	354.6835	0.00
None vs EQ, NPL	275.0159	0.00	LLP vs EQ, NPL, LLP	156.7364	0.00
None vs EQ, LLP	67.1437	0.00	LLP vs EQ, NPL	24.8156	0.00
None vs NPL, LLP	37.476	0.00	LLP vs EQ, LLP	186.4621	0.00
EQ vs NPL	63.0422	0.00	LLP vs NPL, LLP	247.8659	0.00
EQ vs LLP	91.0391	0.00	EQ, NPL, LLP vs EQ, NPL	148.7951	0.00
EQ vs EQ, NPL, LLP	221.2331	0.00	EQ, NPL, LLP vs EQ, LLP	49.9736	0.00
EQ vs EQ, NPL	31.742	0.00	EQ, NPL, LLP vs NPL, LLP	29.2141	0.00
EQ vs EQ, LLP	204.9796	0.00	EQ, NPL vs EQ, LLP	154.6695	0.00
EQ vs NPL, LLP	263.5794	0.00	EQ, NPL vs NPL, LLP	216.5317	0.00
NPL vs LLP	242.8045	0.00	EQ, LLP vs NPL, LLP	24.0305	0.00

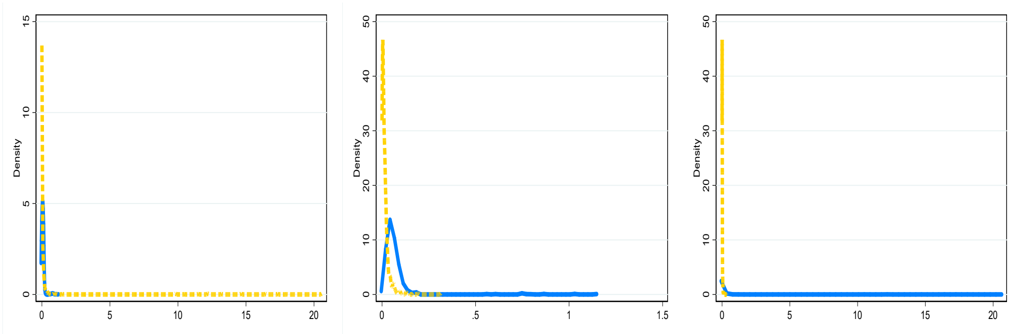
None: no risk variables are included in the cost specification (3.3); EQ: only equity is incorporated as the risk control variable in the cost specification (3.3); NPL: only non-performing loans is incorporated as the risk control variable in the cost specification (3.3); LLP: only loan loss provision is incorporated as the risk control variable in the cost specification (3.3); EQ, NPL, LLP: equity, non-performing loans and loan loss provision are incorporated as the risk control variables in the cost specification (3.3); EQ, NPL: equity and non-performing loans are incorporated as the risk control variables in the cost specification (3.3); EQ, LLP: equity and loan loss provision are incorporated as the risk control variables in the cost specification (3.3); NPL, LLP: non-performing loans and loan loss provision are incorporated as the risk control variables in the cost specification (3.3)

Source: Author's own calculations

Figure 3.4: Density plots for the comparison of efficiency distributions.







The first row (from left to right) shows the distributions of None (yellow dotted line) vs EQ (blue solid line); None vs NPL; None vs LLP; None vs EQ, NPL, LLP; None vs EQ, NPL; the second row is for None vs EQ, LLP; None vs NPL, LLP; EQ vs NPL; EQ vs LLP; EQ vs EQ, NPL, LLP; the third row is for EQ vs EQ, NPL; EQ vs EQ, LLP; EQ vs NPL, LLP; NPL vs LLP; NPL vs EQ, NPL, LLP; the fourth row is for NPL vs EQ, NPL; NPL vs EQ, LLP; NPL vs NPL, LLP; LLP vs EQ, NPL, LLP; LLP vs EQ, NPL; the fifth row is for LLP vs EQ, LLP; LLP vs NPL, LLP; EQ, NPL, LLP vs EQ, NPL; EQ, NPL, LLP vs EQ, LLP; EQ, NPL, LLP vs NPL, LLP; the sixth row is for EQ, NPL vs EQ, LLP; EQ, NPL vs NPL, LLP; EQ, LLP vs NPL, LLP.
Please refer to Table 3.12 for the explanation of all pairs of comparison of eight model specifications.
EQ: equity, NPL: non-performing loans, LLP: loan loss provision.

Source: Author’s own calculations

3.5.2 Discussion of the Overall Results

The proposed cost equation (3.3) with related share equations is estimated by the maximum likelihood estimator utilising the seemingly unrelated regression technique. As previously stated, the Li test demonstrates that Model 5 (which includes all three risk variables) is considered as the best fitted model specification in relation to the efficiency of the Chinese banking sector. Thus, the following discussion is based on the empirical findings of Model 5 and its cost parameter estimates are presented in Table 3.14, which shows that majority of coefficients are statistically significant at the 1% level. Besides, the goodness-of-fit measure (R square) is sufficiently high for the frontier, at a value of 0.967, to justify using the generalised translog functional form in our research. Moreover, Model 5 satisfies all imposed model restrictions (see Table 3.15).

Concerning the monotonicity conditions (monoY1, monoY2 and monoY3) that there must be monotonous increase in outputs, all outputs fulfil this requirement at the mean of the data. The output of gross loans shows the best performance, perfectly matching the condition, with 0% violation. MonoY2 and monoY3 suggest that the marginal costs in terms of other earning assets and loans and advances to banks are also positive. Similarly, the monotonicity restrictions (monoP1, monoP2 and monoP3) that all inputs should have positive partial derivatives are satisfied. Mean values of -0.424, -0.738 and -0.434 are found for personnel expenses, total interest expenses and other operating expenses, respectively. Then, the concavity condition is checked by Allen own input price elasticities, which requires that the value should be negative for all input prices (Tadesse, 2006).

Our findings (see panel B of Table 3.15) are in line with prior work (e.g. Harimaya, 2008; Demirgüç-Kunt and Huizinga, 2013; and Hou, Wang and Li, 2014). All own price elasticities for input prices are negative, and the input demands of P1 and P3 are price elastic, while P2 shows a minor degree of price inelasticity. The associated violations are also low throughout the three input prices, ranging from 0.00% to 0.51%. This indicates that equation (3.3) corroborates the vital assumption about the concavity restriction: that the cost function is globally concave in each of the factor. Next, Allen cross price elasticities are estimated in order to further illuminate the nature of production processes in the Chinese banking industry. Normally, inputs are deemed to be complements if a negative sign is observed for partial elasticities, while a positive sign means that inputs are substitutes (Brown and Glennon, 2000).

The results are exhibited in panel C of Table 3.15 (i.e., PE12, PE13 and PE23), where the values are calculated at the point constituting the 'average' bank in the sample. P2 is shown to be a strong substitute for each of the other variables, given that PE12 and PE23 indicate a strong substitutability between P1 and P2, P2 and P3. Moreover, PE12 and PE23 present a similar degree of such substitution effects. A negative elasticity value between P1 and P3 implies that they are complements for each other. Overall, Table 3.15 provides assurance that the use of the translog functional form is appropriate and our representation of the production technology of the Chinese banking sector is reasonable and comparable to experiences in other economies.

The following part of this section moves on to describe in greater detail the evaluation of the degree of scale economies in banks. The scale economies estimated by equation (3.9) for examined banks across the sample period are presented in Table 3.16.

Overall, minor diseconomies of scale are discovered for sample banks, given that the mean value of scale economies across all sample is 1.041. That is, industry-wide diseconomies of scale are found for the Chinese banking industry[100]. These empirical findings are in accordance with the results documented in Meslier, Tacneng and Tarazi (2014), where diseconomies were found for Chinese commercial banks, which was attributed to those banks facing increasingly higher monitoring and capital costs over the observation period. Indeed, when our sample banks experienced reduced non-performing loans and relaxed capital requirements over the period 2005 to 2011 (see

[100] The estimates of scale economies for all sample banks across each observation year are offered in Table 7.5 in appendix A.

Figure 3.3), their observed cost diseconomies decreased (see Table 3.16). Conversely, this diseconomy grew with the deterioration of non-performing loans and strengthening of bank capitals from 2012 to 2015.

In addition, the sample banks enjoyed slight economies of scale between 2009 and 2012, reflecting the decrease in external costs in relation to their expansions in size. During this period, banks' operating costs (with the reduced extra risk-taking due to the GFC) were more efficiently spread over banks' larger outputs. Then the diseconomies set in, along with increased capital costs in the Chinese banking sector. The data allow us to identify that the four large state-owned commercial banks – Agricultural Bank of China, China Construction Bank, Industrial and Commercial Bank of China and Postal Savings Bank of China – are found to have enjoyed considerable economies of scale throughout the sample period, with mean estimates of 0.80, 0.90, 0.88 and 0.71 respectively over the study period. The finding that large banks are able to exploit economies of scale differs from many previous studies which concluded that only banks with smaller asset size can experience scale economies (e.g., Margono et al., 2010; Hadad et al., 2013; Davies and Tracey, 2014; and Doan, Lin and Doong, 2018).

On the one hand, Wheelock and Wilson (2012) suggest that larger banks are capable of reducing their expenses more efficiently than smaller banks because they have broader sectoral and geographic diversity. That is, greater diversification allows those banks to reduce risk, while spreading overhead expenses, lessening risk-management costs, and exploiting increased network economies will all work to boost expected margins. On the other hand, the cost-of-funds subsidies because of 'too big to fail' considerations may also explain the estimated increasing returns to scale of the above four banks[101]. Generally, the central government offers advantages to these systematically important financial institutions. For example, these institutions are provided with financial internal economies of scale by borrowing funds at a lower rate than their competitors (Beccalli, Anolli and Borello, 2015).

[101] Agricultural Bank of China, China Construction Bank, and Industrial and Commercial Bank of China have all appeared on the annual G-SIBs (global systematically important banks) list produced by the Financial Stability Board since 2015.

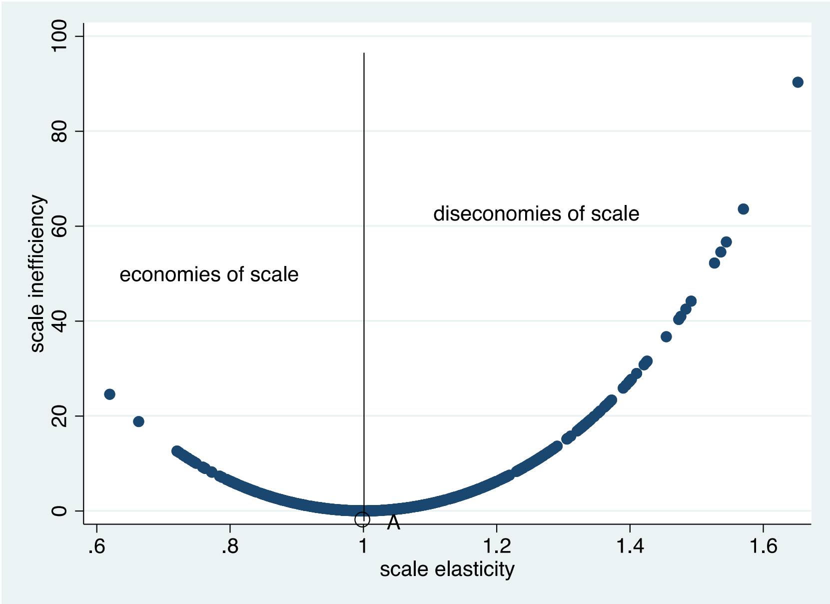
From an international perspective, we observed lower diseconomies of scale in Chinese banks than banks in advanced EU economies, which were severely hit by two financial crises[102]. For instance, a mean estimate of 1.494 of decreasing returns to scale is reported by Rossi and Beccalli (2020) for banks in the UK over 2005 to 2018. An average of 1.133 and 1.169 are reported for Danish and German banks respectively in the same paper.

We turn now to the empirical results of scale inefficiency estimation of sample banks. The concept of scale efficiency points out whether banks operate at the optimum scale, given similar production technology. This measure indicates how sample banks manage their operational expenses in relation to changes in outputs (Hou, Wang and Li, 2014). A bank, normally, is perceived to be perfectly scale-efficient if any size adjustments will cause the bank to be less efficient.

In the presence of either increasing or decreasing returns to scale, banks will experience scale inefficiency. By plotting the relation between the measures of scale economies and scale efficiency, Figure 3.5 shows that sample banks are compelled to lie on a symmetric U-shaped ray average cost frontier. Point A represents banks that operate with 0% of scale inefficiency, while displaying constant returns to scale. Accordingly, the best-performing scale-efficient banks should have scale economies estimates infinitely approaching a value of 1. It can be clearly seen in Figure 3.5 that bank scale inefficiency scores increase as the diminishing (or increasing) scale effects of sample banks rise. Moreover, those banks exhibiting diseconomies of scale contribute roughly 55% of the observed inefficiency; the rest is attributed to banks that operate under increasing returns to scale economies.

[102] The GFC and the following the European sovereign debt crisis.

Figure 3.5: Plot of scale elasticity and scale inefficiency estimates.



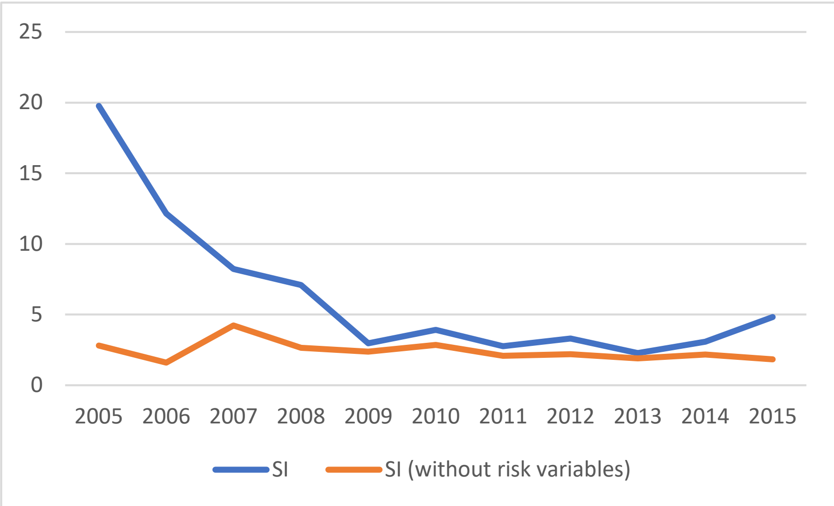
Scale elasticity is estimated through equation (3.9), and scale inefficiency is estimated through equation (3.17).

Source: Author's own calculations

With respect to the inefficiency estimates (calculated using equation 3.17), Table 3.16 exhibits the estimation results for the full sample over the study period. During 2005 to 2009, bank scale efficiency increased substantially, reflected by an 85% (from 19.77% to 2.98%) reduction in the estimates of inefficiency. Within this time period, in order to minimise costs, sample banks endeavoured to adjust their asset size to operate at the optimum scale. From 2009, Chinese banks started to recognise an excellent efficiency performance, and that favourable performance was well maintained in the following four years. Next, we witness a slight deterioration in efficiency, with the inefficiency score increasing from 2.78% to 4.82% over the period 2013 to 2015.

By comparing the column SE and SI of Table 3.16, it can be seen that scale elasticity and scale efficiency are two distinct measures and use of the elasticity alone to approximate the level of efficiency is inadequate for Chinese banks. Our study offers an empirical example (by computing an inefficiency metric) to distinguish between these two concepts. Another assumption that has been validated during our estimation is that ignoring risk considerations in the cost specification can lead to biased efficiency estimates for banks (see Figure 3.6). The findings show that the inclusion of the costs of financial risk noticeably decreases estimated efficiency for sample banks, especially for the period 2005-2009. Our results demonstrate that equity, non-performing loans and loan loss provision are indeed significant factors required for the analysis of the intermediation (production) process of the Chinese banking system.

Figure 3.6: Evolution of scale inefficiency estimates.



SI: scale inefficiency, estimated through equation (3.17), SI (without risk variables): scale inefficiency estimates when the three risk control variables are excluded from the cost specification (3.3).

Source: Author's own calculations

Theoretical models of financial intermediation[103] also indicate that one of the most important sources of financial returns to scale in banking is asset diversification, which lessens the amount of expensive financial equity that an intermediary has to keep in order to operate (see, for example, McAllister and McManus, 1992; Hughes and Mester, 2013; and Hou, Wang and Li, 2015). When the relationship between risk, diversification, and size is appropriately accounted for, more accurate and consistent scale-related effects in Chinese banking can be derived. For instance, it is the neglect of risk variables in the majority of the earlier banking literature on scale efficiency that led to them detecting diseconomies of scale for larger banks (or, conversely, economies

[103] It should be mentioned again that our estimation follows the intermediation approach to define the bank input-output mix utilised in the cost function.

of scale for smaller banks). As discussed above, we, instead, find strong evidence of scale economies even for the largest Chinese state-owned commercial banks. This relation between bank size and scale efficiency is explained in greater detail in the next section.

Table 3.14: Estimated cost parameters for equation (3.3).

	Coefficient	Std. error		Coefficient	Std. error
lnp1	0.190***	0.003	*lnnpllnp1*	0.005***	0.002
lnp2	0.634***	0.005	*lnnpllnp2*	-0.010***	0.004
lnp3	0.176***	0.003	*lnnpllnp3*	0.006***	0.002
lny1	0.577***	0.057	*lnnpllny1*	-0.010	0.024
lny2	0.330***	0.024	*lnnpllny2*	0.003	0.014
lny3	0.047**	0.023	*lnnpllny3*	0.011	0.017
lnp1lnp1	0.116***	0.001	*lnllplnp1*	0.004*	0.002
lnp2lnp2	0.085***	0.003	*lnllplnp2*	-0.007*	0.004
lnp3lnp3	0.118***	0.002	*lnllplnp3*	0.004*	0.002
lnp1lnp2	-0.041***	0.001	*lnllplny1*	-0.001	0.025
lnp1lnp3	-0.075***	0.001	*lnllplny2*	0.037***	0.009
lnp2lnp3	-0.043***	0.001	*lnllplny3*	-0.047**	0.019
lny1lny1	0.240**	0.109	*t*	-0.004	0.007
lny2lny2	0.027***	0.008	*t2*	-0.031***	0.005
lny3lny3	0.063***	0.013	*tlneq*	-0.010	0.016
lny1lny2	-0.128***	0.037	*tlnnpl*	0.010	0.006
lny1lny3	-0.056***	0.046	*tlnllp*	-0.012**	0.006
lny2lny3	-0.033***	0.021	*t2lneq*	-0.027***	0.006
lny1lnp1	-0.009***	0.005	*t2lnnpl*	0.015***	0.003
lny1lnp2	0.020***	0.010	*t2lnllp*	-0.025***	0.004
lny1lnp3	-0.011***	0.005	*tlnp1*	-0.010***	0.001
lny2lnp1	-0.007***	0.002	*tlnp2*	0.019***	0.001
lny2lnp2	0.009***	0.003	*tlnp3*	-0.008***	0.001
lny2lnp3	-0.002	0.002	*t2lnp1*	-0.001***	0.000
lny3lnp1	-0.017***	0.002	*t2lnp2*	0.002***	0.001
lny3lnp2	0.031***	0.004	*t2lnp3*	-0.001	0.000
lny3lnp3	-0.014***	0.002	*tlny1*	0.056***	0.016
lneq	-0.055	0.051	*tlny2*	-0.037***	0.006
lneqlneq	-0.044	0.089	*tlny3*	-0.012	0.008
lneqlnp1	0.028***	0.005	*t2lny1*	0.031***	0.009
lneqlnp2	-0.050***	0.009	*t2lny2*	0.000	0.004
lneqlnp3	0.022***	0.004	*t2lny3*	-0.003	0.005
lneqlny1	-0.227***	0.074	*tlny1lny1*	0.006	0.015
lneqlny2	0.226***	0.034	*tlny2lny2*	-0.007**	0.003

lneqlny3	0.073*	0.041	*tlny3lny3*	-0.013***	0.005
lnnpl	0.040**	0.020	*tlny1lny2*	-0.001	0.007
lnnpllnnpl	0.020**	0.009	*tlny1lny3*	-0.002	0.010
lnllp	0.122***	0.026	*tlny2lny3*	0.011	0.008
lnllplnllp	-0.011	0.015	*_cons*	7.918***	0.025
			R-sq	0.967	
share1			*share2*		
lnp1	0.116***	0.001	*lnp1*	-0.041***	0.001
lnp2	-0.041***	0.001	*lnp2*	0.085***	0.003
lnp3	-0.075***	0.001	*lnp3*	-0.043***	0.001
lny1	-0.009*	0.005	*lny1*	0.020**	0.010
lny2	-0.007***	0.002	*lny2*	0.009***	0.003
lny3	-0.017***	0.002	*lny3*	0.031***	0.004
lneq	0.028***	0.005	*lneq*	-0.050***	0.009
lnnpl	0.005**	0.002	*lnnpl*	-0.010***	0.004
lnllp	0.004*	0.002	*lnllp*	-0.007*	0.004
t	-0.010***	0.001	*t*	0.019***	0.001
t2	-0.001***	0.000	*t2*	0.002**	0.001
_cons	0.190***	0.003	*_cons*	0.634***	0.005
R-sq	0.581		*R-sq*	0.506	

*Note: *** significant at the 1% level, ** significant at 5%, * significant at 10%.*

Where lnp1: price of labour (measured as personnel expenses/ fixed assets), lnp2: price of average customer deposits (measured as total interest expenses/average customer deposits), lnp3: price of capital (measured as other operating expenses/fixed assets), lny1: gross loans, lny2: other earning assets, lny3: loans and advances to banks, lneq: equity, lnllp: loan loss provision, lnnpl: non-performing loans. All values are expressed in natural logarithms. And t: time trend term, t2: the square of time trend term.

Source: Author's own calculations

Table 3.15: Regulatory conditions as a check for equation (3.3).

Panel A	Mean	Std. error	Violation
monoY1	0.656***	0.005	0.00%
monoY2	0.249***	0.002	1.02%
monoY3	0.168***	0.003	2.54%
monoP1	0.277***	0.004	0.51%
monoP2	0.464***	0.008	4.96%
monoP3	0.258***	0.004	0.00%
Panel B			
PE11	-0.424***	0.017	0.51%
PE22	-0.738***	0.009	0.00%
PE33	-0.434***	0.003	0.25%
Panel C			
PE12	1.413***	0.094	
PE13	-1.710***	0.116	
PE23	1.414***	0.095	

*Note: *** significant at the 1% level, ** significant at 5%, * significant at 10%.*
Where mononY1: monotonicity condition for Y1, mononY2: monotonicity condition for Y2, mononY3: monotonicity condition for Y3, mononP1: monotonicity condition for P1, mononP2: monotonicity condition for P2, mononP3: monotonicity condition for P3, PE11: Allen own price elasticity for P1, PE22: Allen own price elasticity for P2, PE33: Allen own price elasticity for P3, PE12: Allen cross price elasticity for P1 and P2, PE13: Allen cross price elasticity for P1 and P3, PE23: Allen cross price elasticity for P2 and P3, Y1: gross Loans, Y2: other earning assets, Y3: loans and advances to banks, P1: X1 / fixed assets, P2: X2 / average customer deposits, P3: X3 / fixed assets.

Source: Author’s own calculations

Table 3.16: Estimation results for equations (3.9) and (3.17) of Model 5.

Year	SE	Std. error	SI	Std. error
2005	1.329***	0.093	19.77%	12.398
2006	1.238***	0.128	12.15%	12.310
2007	1.158***	0.151	8.22%	15.818
2008	1.099***	0.181	7.10%	11.401
2009	0.978***	0.137	2.98%	3.579
2010	0.962***	0.151	3.92%	7.472
2011	0.967***	0.128	2.75%	4.540
2012	0.977***	0.141	3.31%	7.548
2013	0.997***	0.121	2.28%	3.408
2014	1.060***	0.126	3.08%	4.796
2015	1.125***	0.119	4.82%	7.349
whole sample	1.041***	0.159	4.42%	8.098

*Note: *** significant at the 1% level.*
SE (scale elasticity) is estimated through equation (3.9), SI (scale inefficiency) is estimated through equation (3.17). All values are estimated at the mean of the data.
The t test is performed for SE estimates with the null hypothesis that the mean equals one.
See Table 3.12 for the definition of Model 5.

Source: Author's own calculations

3.5.3 Results by Asset Size

There is no agreed conclusion regarding the interaction between bank size and scale economies. On the one hand, a significantly positive association has been documented in a few empirical papers. For instance, Wheelock and Wilson (2012) examine whether bigger US banks have lower operational costs. They find that economies of scale increased as the asset size of US banks increased over the period 2000 to 2006. Larger US banks (even several global US banking institutions) could benefit from their huge asset size and experience greater productivity gains than smaller banks across the sample period. Zha et al. (2016) examine the scale and X-efficiency of the Chinese banking sector, and find that large Chinese state-owned and joint-stock banks are the best practice banks that define the technology frontier and allocate their costs in the sample. Tadesse (2006) recorded similar evidence for the Japanese banking industry. His paper points out that technological advances and better diversification produce increasing returns to scale for large Japanese state banks.

On the other hand, employing various datasets, numerous empirical studies have offered evidence of scale economies among smaller banks (e.g., Davies and Tracey, 2014; Luo, Tanna and De Vita, 2016; Doan, Lin and Doong, 2018; and Nguyen, 2018). Moreover, lately, an increasing number of studies have expressed concern about 'too big to fail' subsidies for large banking institutions and suggest that banks suffer from diminishing returns to scale once a certain size is exceeded (see Davies and Tracey, 2014 and Bitar, Pukthuanthong and Walker, 2018). Generally, these papers argue that the further expansion of banking outputs (e.g., other earning assets) normally will be followed by an increase in associated charges. If the cost inefficiency arises as a result, banks with asset size that exceeds their optimum level can gradually lose the advantage of scale economies.

In accordance with the above viewpoint, in their study of German banks, Schmaltz et al. (2014) demonstrate that large systematically important banks entail higher implicit regulatory costs[104]. Thus, diseconomies of scale were present for those banks during the sample period, while smaller banks continued to grow (through horizontal or vertical integration) to exploit scale economies. In our sample, slightly diminishing economies of scale are reported for the full sample, with a reasonable level of efficiency performance (see Table 3.16). To deepen our examination, as was pointed out in the introduction to this chapter (section 3.2), sample banks are grouped on the basis of asset size to further investigate scale effects.

Banks, as asset transformers, are in a multi-product industry in which they choose to specialise in the production of a limited number or a full range of financial services. In consequence, different banks to employ those production methods which best fit their provided services, insofar as they are consistent with their operational strategic plans. That is, banks' production technology is determined by their specific strategic conduct, and in turn their choices of strategic conduct define their adopted production technology and ultimately determine their cost structure. Badunenko and Kumbhakar (2017) argue that this might be the primary motivation for banking comparative studies to classify banks into peer groups and compare the differences between groups.

Banking size is one of the most commonly used proxies for product mix to segment the entire sector into groups with similar production technologies (see Bryce et al., 2015; Aysun, 2016; and Laeven, Ratnovski and Tong, 2016). There are three main reasons to stratify banks by size: (i) it is widely accepted that asset size is highly related with banks' funding and investment behaviours – size indicates a difference in banking activities (e.g., bigger banks are more likely to have distinctive portfolios compared with smaller banks); (ii) it is a clear and simple criterion, whereby banks are or are not in a group determined by pre-established boundaries and there is no uncertainty regarding placement; and (iii) the groups are relatively stable over time, which means banks normally stay in the same group throughout a study period.

[104] Their paper reports that all four regulatory ratios (i.e., capital adequacy ratio, leverage ratio, net stable funding ratio and liquidity coverage ratio) impose significantly negative effects on the scale efficiency estimation of large German banks.

Accordingly, we split sample Chinese banks into four quartiles in terms of their asset size for a comparative analysis (see Table 3.17). To obtain a preliminary understanding of our sample, first, the cost relationship of the overall sample is shown in Figure 3.7, where a scatter diagram plots the average cost[105] against the log of total assets of sample banks. It shows that cost seems to vary widely across the smaller banks and varies less as bank size increases. Nevertheless, there are outliers in the sample with abnormally high values of average cost (e.g., China Ping An Bank[106]). Figure 3.8 shows that the average costs of sample banks decline as bank size increases, indicating that banks' costs are normally reduced with the expansion of their asset size. This might be a sign of scale economies for larger Chinese banks in the sample.

Table 3.17: Four bank groups by quartiles of assets (CNY million).

Quartiles	Percent	Min	Max
Asset Group 1	24.67	89.6	20224.469
Asset Group 2	25.21	20227.371	49584.623
Asset Group 3	24.97	49590.346	131022.17
Asset Group 4	25.15	131080.5	15151252

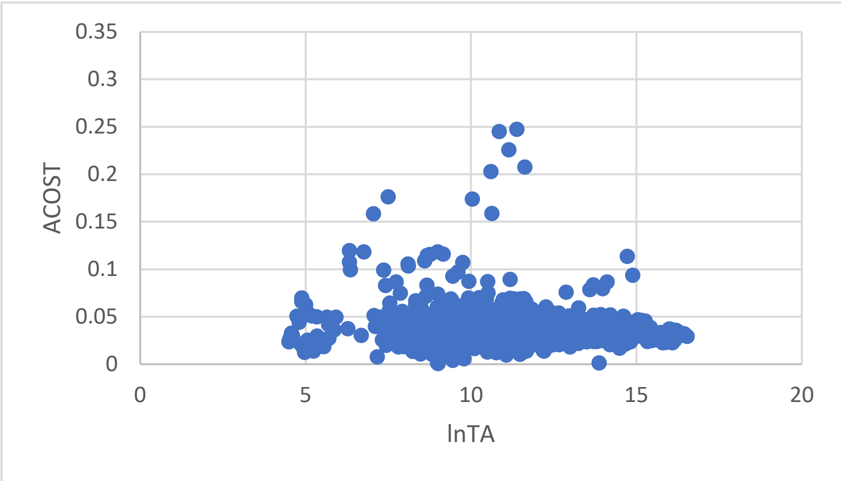
Where Asset Group 1 are the sample banks in the lowest quartile (banks with the lowest average asset size) and Asset Group 4 are the sample banks in the highest quartile (banks with the highest average asset size).

Source: Author's own calculations

[105] The average cost (ACOST) is the operating and interest costs per dollar of assets, measured as the sum of total interest expenses and total non-interest expenses divided by bank total earning assets.

[106] During 2009 to 2012, China Ping An Bank continued to expand its operation by merging with another institution, Bank of Shenzhen. Normally, M&A entails substantial restructuring costs for the banks involved, for instance, the costs that arise during the integrating process and the costs of inventory and appraisal of assets.

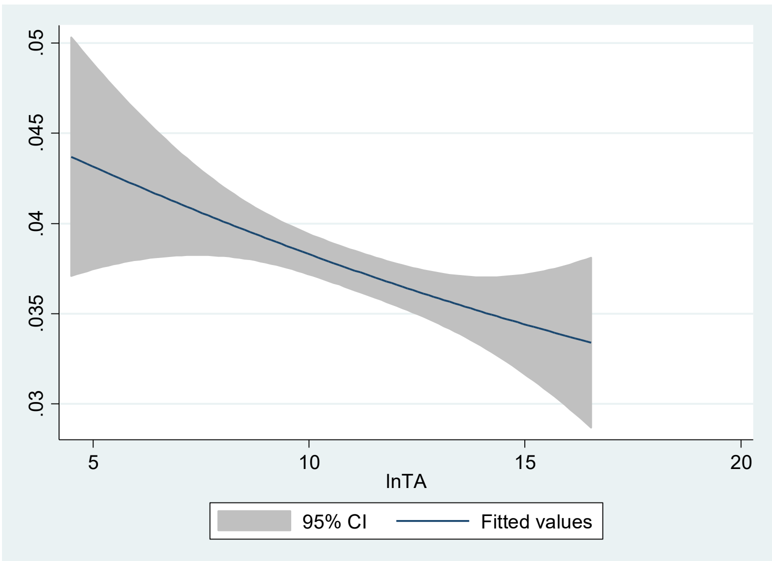
Figure 3.7: Average costs of sample banks.



Where ACOST is measured as the sum of total interest expenses and total non-interest expenses divided by bank total earning assets and lnTA is the logarithm values of bank total assets.

Source: Author’s own calculations

Figure 3.8: Plot of ACOST and lnTA of sample banks.

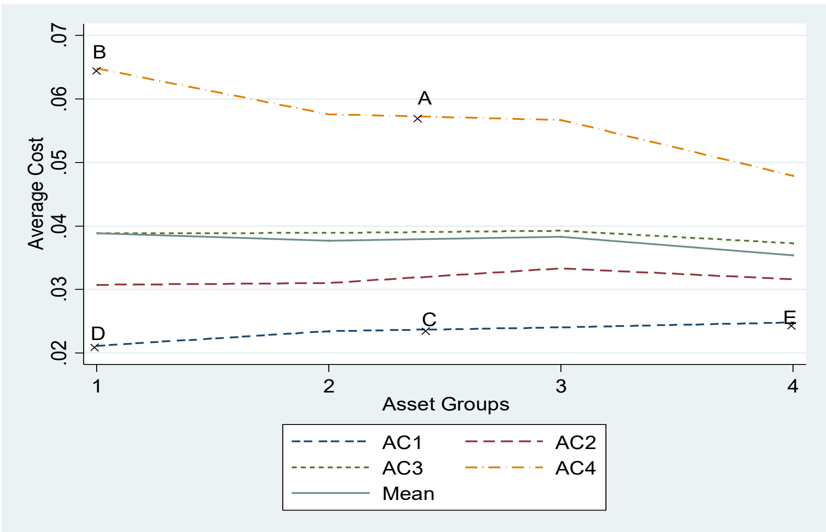


ACOST: average cost of banks (measured as the sum of total interest expenses and total non-interest expenses divided by bank total earning assets), lnTA: logarithm values of bank total assets.

Source: Author’s own calculations

Sample banks are sorted by their average cost into four cost quartiles in Figure 3.9, where AC1 is the average cost of the 25% of sample banks in each of four generated size groups with the lowest (first quartile) individual average costs, and the AC4 displays the mean cost of all banks within the highest (fourth quartile) average cost class. Overall, the four bank asset groups show a noticeable cost dispersion only in the highest cost class – the larger the size, the lower its average cost. Moreover, Figure 3.9 shows that cost variations between the highest and lowest cost quartiles (AC4 and AC1) in any given asset size group are much larger than there those between the highest and lowest average cost values in any given cost quartile across all size groups. For instance, the difference between point A and C is the cost difference between AC4 and AC1 within the asset group 3, and its value is always greater than the maximum variation along a size group, such as the difference between point A and point B on the AC4 line, or between points D and E on the AC1 line.

Figure 3.9: Average cost quartiles across each asset group.

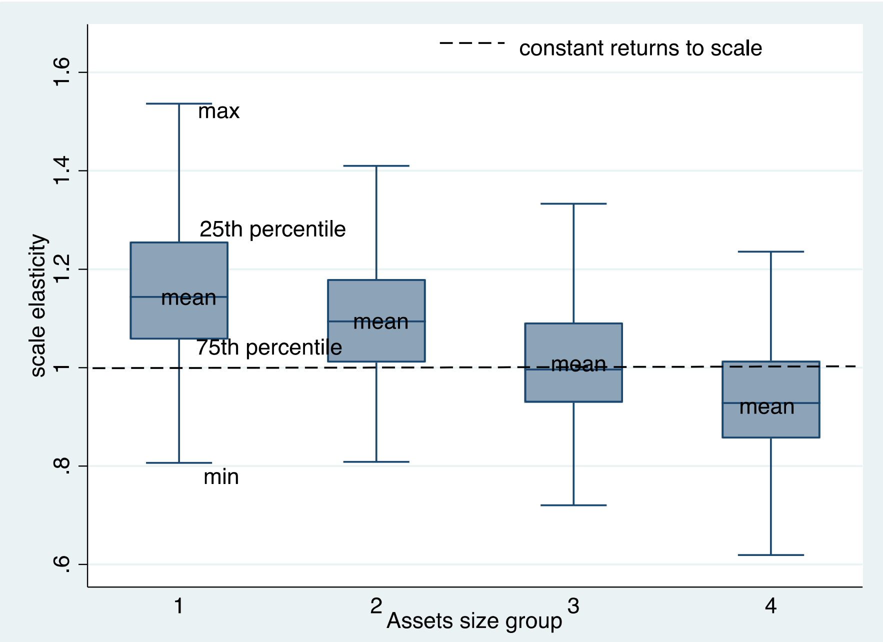


The solid line ('Mean') is the mean average cost for all banks in each size group over all four quartiles together.

Source: Author's own calculations

Tables 3.18 and 3.19 present the measures of scale economies and scale inefficiency for the sample banks in each size group at each observation year. The corresponding graphical representations are in Figures 3.10 and 3.11. Figure 3.10 shows that banks in asset group 1 (smallest banks) on average show the highest diminishing returns to scale, and this group has the largest variations with regard to scale elasticity. For about 90% of observations in asset group 2, the values of elasticities are within the range of 1 to 1.2. The group's mean scale elasticity measure (1.099) is smaller than that of group 1 (1.160). Roughly 40% of the banks in asset group 3 generate increasing returns to scale while the remainder of the banks in this category show diseconomies of scale. Its average estimate (1.016) implies that those banks are operating fairly close to the optimum level, given their specific production technology. Regarding the banks in asset group 4, most of them enjoy noticeable economies of scale – demonstrating that these banks should expand their balance sheets to achieve cost reductions.

Figure 3.10: Scale elasticity estimates across each size group.



See the definition of asset size group in Table 3.17.
Scale elasticity is estimated through equation (3.9).

Source: Author's own calculations

Overall, diseconomies of scale are observed for the smallest and medium-small banks, increasing returns to scale are reported for the banks with the largest asset size and constant returns to scale are witnessed for medium-large banking institutions. Consequently, those banks whose assets values are between CNY49,590.346 million and CNY131,022.17 million seem to be the ones with the best practice, capable of transforming bank inputs into outputs at the minimum average cost level. Our results also shed light on the economic rationale for the recent M&A trend in the Chinese banking sector[107], since there are economies of large-scale production for bigger Chinese banks. We suggest that industry-wide efficiency could be gained through the consolidation of efficient larger banks with inefficient smaller banks.

As explained in section 3.5.2, TBTF subsidies contribute to the economies of scale experienced by larger banks through the lowered funding costs. Indeed, those banks might take advantage of lower levels of funding costs when they are perceived by investors to be too big to fail. For example, bank debt holders loosen the risk premium requirements on debts due to expectations of explicit or implicit government support for these banks in the case of financial distress. This argument has received increasing attention since the GFC and is supported by several empirical studies, including Tadesse (2006), Hughes and Mester (2013) and Davies and Tracey (2014).

Banks might still choose to expand, regardless of diminishing returns to scale, in order to gain TBTF subsidies if these will outweigh any scale diseconomies – as indicated by critics of the largest banks (Davies and Tracey, 2014). To investigate whether the estimated scale economies of larger banks are driven purely by TBTF subsidies, Hughes and Mester (2013) propose the following approach. Employing a sample of US banks, they first calculate the scale elasticity measures of the full sample for the year of 2007. The corresponding estimates are listed by 6 asset size groups[108], and a mean of 0.749

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[107] On average, over 2010-2015, Chinese banks completed M&A deals with an aggregate worth of USUS$ 625.85 million, ranking China in second across world nations in terms of aggregate deal values, on the SNL-generated worldwide bank M&A heat map. The first place belonged to US banks, whereas UK and Hong Kong banks stood in third and fourth place. Normally, consolidation entails substantial restructuring costs for the banks involved, for instance, the costs that arise during the integrating process and the costs of inventory and appraisal of assets. Bank managers tend to believe that they can attain cost efficiency gains if scale and scope economies can be achieved (Pessarossi and Weill, 2015). In the long run, banks can benefit from M&A in terms of increasing market power and realising scale and scope economies.

[108] Utilising the data of the US banking in 2007, Hughes and Mester (2013) partition the full sample into 6 groups based on bank's consolidated assets value. Group 1 consists of US banks whose assets value are less than US$0.8 billion, while group 2 contains banks with asset size between US$0.8 and US$2 billion. The remaining 4 groups take the size range of US$2-US$10 billion, US$010-US$50 billion, US$50-US$100 billion and larger than US$100 billion.

is obtained for the size group that has the largest assets value (over US$100 billion in assets). Following Brewer and Jagtiani (2009), they find that the banks whose assets value exceed US$100 billion are the TBTF banks in the sample. The cost equation is then re-estimated after eliminating these banks from the sample. On the basis of the fitted cost equation, scale elasticities are computed for the out-of-sample group of TBTF banks.

This method generates an elasticity of 0.742 for the group of largest US banks. If these biggest banks save costs through a lowered level of funding expense, their exclusion and the out-of-sample estimation of virtually the same scale elasticity offers convincing empirical evidence that the approximated scale economies for these largest institutions are not being driven by TBTF considerations.

Our study uses a similar method to verify whether TBTF subsidies or technological factors are the main contributor to the presence of increasing returns to scale among the largest Chinese banks. Hughes and Mester (2013) demonstrate that the use of US$100 billion as the threshold assets value for the recognition of TBTF banks is sensible for the US banking sector. However, there seems to be no evidence to support the use of the same value for Chinese banks. Besides, as was pointed out in section 3.3.2, bank size is not the sole determinant of too big to fail.

We therefore follow the PBOC (2017) stress testing bank list, discussed in section 3.3.2 to identify Chinese TBTF banking institutions. To recap, according to the PBOC's definition, banks on the test list are classified as D-SIBs in the Chinese banking system and thereby these banks[109] are TBTF because of their systemic importance (see Table 3.5). Once these banks have been identified, first, our cost function (3.3) is estimated for the sample of financial institutions that are not deemed to be 'systemically important' (TBTF). These parameter estimates are utilised to measure the scale economies for the full sample including those D-SIBs that are perceived to possess TBTF subsidies. The aim is to determine the value of the coefficients for the cost equation

[109] Refer to footnote 84 for the full list of these 15 banks.

(3.3) when its estimation is free from TBTF considerations. Table 3.18 (see row Full sample#) shows the corresponding parameter estimates. The values of the estimated scale elasticities for each asset group increase slightly, but, still, economies of scale (0.963) are observed for asset group 4 (Chinese banks with the largest assets)[110].

Moreover, Hughes and Mester (2013) propose that the evidence on the estimated scale economies is motivated by TBTF subsidies could be the finding of increasing returns to scale at those largest TBTF banks is driven by considerations of lower costs of funds, and that if these banks faced the same funding expenditure as smaller banks, they would not have the competency to exhibit economies of scale. To verify above assumption, we assume the funding costs (three input prices) of these 15 D-SIBs in our sample to take the median values of input costs of the sample banks that are not perceived to be TBTF. Scale elasticity is then computed for the group of TBTF banks in the sample. Again, significant scale economies (with an estimate of 0.872) are observed.

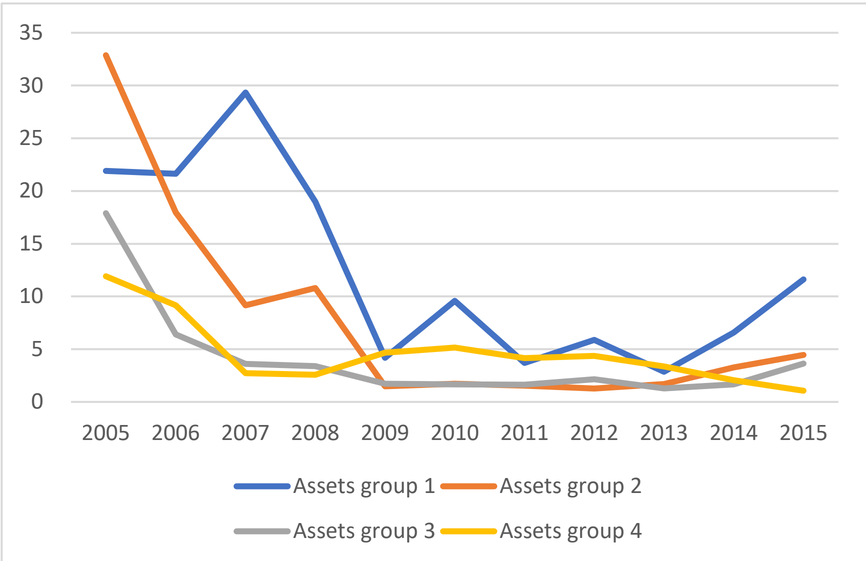
Hence, the cost savings achieved by these largest banks in our sample indeed indicate a scale economy, instead of a representation of expectation of advantageous treatment of TBTF banks by the authorities. In this case, the policy restrictions that imply downsizing of financial institutions may cause competitive disadvantage for large banks in China in light of the scale economies forgone. The optimum scale of banks, as regulated institutions, is a question of public policy. Davies and Tracey (2014) suggested that "*a full answer needs to balance the benefits of scale with the costs of scale due to potential increases in systemic risk and crisis costs*" (page 244). Hughes and Mester (2015) use a similar argument when they point out that "*size restrictions may not be effective since they work against market forces and create incentives for firms to avoid them. Avoiding the restrictions could thereby push risk-taking outside of the more regulated financial sector without necessarily reducing systemic risk. If such limits were imposed, intensive monitoring for such risks would be required*" (page

[110] Whereas the scale elasticity measure is found to be 0.931 (with a 1% significance level) for the 15 TBTF banks (not in asset group 4) in the sample.

1).

With regard to estimated scale inefficiencies across each asset group, Table 3.19 and Figure 3.11 show that asset group 1 has the largest mean value of inefficiency (8.7%) among the 4 size groups, indicating that these smallest banks on average are the least scale-efficient banks in the sample. Moreover, about 80% of observations in this size group have values of the inefficiency estimate larger than the group's mean value. Banks in groups 2 and 4 present similar efficiency performance, while the mean of inefficiency is slightly higher for asset group 2 (4.16%) than for asset group 4 (3.65%). In line with our findings on scale elasticities of sample banks, asset group 3 contains those banks whose asset size are closest to optimal, given that this group produces the smallest mean inefficiency score (2.85%). The inefficiency estimates for this group vary the least across 4 size groups, as the values are concentrated near the group's average value.

Figure 3.11: Scale inefficiency estimates across each size group (%).



See the definition of asset size group in Table 3.17; scale inefficiency is estimated through equation (3.17).

Source: Author's own calculations

Furthermore, noticeable cost variations are observed across different asset quartiles compared with variations among size groups within a quartile (see Figure 3.9). This indicates a large variation in average costs for banks within the largest asset quartile, where their scale variations are relatively small (see Figure 3.11). The size of these variations indicates that Chinese banks are not close to being equally efficient. In particular, for the group of largest banks, regulatory factors, such as the entry barriers created by branching and charter restrictions and the deposit insurance scheme, may have allowed inefficiencies to grow. Moreover, as discussed in Chapter 2, the deregulation and increasing competition in the Chinese banking industry have provided opportunities for the rapid development of Chinese banks. Accordingly, the scale efficiency performance of each group of sample banks tended to improve overall prior to the year 2012, as the heated competition squeezed out inefficiency in these financial institutions, and banks also became more specialised in their operations (see Table 3.19). Since then, however, inefficiencies have set in, suggesting that the asset size of Chinese banks was deviating from the optimum.

Concerning the estimation of technological change, Table 3.20 gives the estimates obtained for sample banks across each asset group, while Table 3.21 displays the results for tested banks in observation year. As shown in Table 3.20, we observe significant technological advancement in medium-small and medium-large Chinese banks, given that medium-small banks (in asset group 2) show a rate of THC of 0.005 and medium-large banks (in asset group 3) exhibit a mean value of 0.023. That is, a reduction in expenditure at a rate of 0.5% can be attained by banks in asset group 2 as a result of technological change, and banks in asset group 3 can enjoy a 2.3% annual decrease in total costs. The smallest sample banks in asset group 1 and the overall sample exhibit no technological change.

By comparing estimates of THC between asset groups 2 and 3, we find that bigger Chinese banks experience higher cost savings (owing to technological change) than smaller banks. Our finding contrasts with the argumentation proposed by Simper, Dadoukis and Bryce (2019), whose study explores progress in technological innovative by European banks over the period 2002-2014. Their results suggest that "*small and medium sized banks innovate at a faster rate than the largest banks as the latter can rely on a large customer based and branch network – exploiting market power for* *profitability. Whereas smaller banks rely on being agile in the face of innovation to counteract scale inefficiencies (being too small in asset size) to fund operations, reduce capital costs, and implement new technologies to reduce costs*" (page 123). Instead, in our sample, larger banks exploit technological progress to a greater extent than smaller banks to minimise their average costs.

Moreover, Table 3.21 shows that significant technological advancement is found for sample banks only from 2012; the rate of THC steadily improved from 1.2% in 2012 to 7.6% in 2015. Regarding the scale-biased estimates (TSB), from Table 3.20, the full sample produces a mean of TSB of 0.7%, confirming the presence of scale-biased technological change amongst Chinese banks. This means that the cost-minimising efficient bank scale has been altered (increased) due to TSB. The bias, in turn, leads to cost savings for sample banks at an increasing rate over 2012 to 2015 (increased from 2.7% in 2012 to 11.8% in 2015 – see Table 3.21). Our results further demonstrate that such impact increases in line with the size of banks. For instance, we document a rate of TSB of 0.7% for banks that are grouped into the second asset quartile, while higher rates, of 0.8% and 1.1%, are obtained for banks in the third and fourth asset quartiles.

Overall, our research shows that technological innovation in the Chinese banking industry has improved the comparative advantages of large-sized operations in the system. Consistent with studies in the US and European countries (advanced economies), our analysis provides evidence that industry consolidation has resulted from Chinese large banks seeking to continue to expand their systemic size, not only as a way to resolve distress from the GFC but also to improve the system efficiency of the Chinese banking sector.

Table 3.18: Estimated scale elasticities in each asset size group.

Year	**Asset group 1**	Std. error	**Asset group 2**	Std. error	**Asset group 3**	Std. error	**Asset group 4**	Std. error
2005	1.372***	0.033	1.422***	0.045	1.325***	0.020	1.259***	0.039
2006	1.353***	0.033	1.305***	0.078	1.193***	0.026	1.182***	0.058
2007	1.348***	0.089	1.225***	0.028	1.134***	0.027	1.060***	0.032
2008	1.303***	0.056	1.225***	0.034	1.047***	0.034	0.958***	0.031
2009	1.119***	0.039	1.051***	0.022	0.931***	0.021	0.885***	0.031
2010	1.106***	0.066	1.028***	0.025	0.923***	0.015	0.869***	0.029
2011	1.089***	0.032	1.005***	0.024	0.946***	0.018	0.891***	0.024
2012	1.088***	0.037	1.034***	0.017	0.936***	0.021	0.884***	0.022
2013	1.096***	0.025	1.062***	0.017	0.967***	0.017	0.910***	0.022
2014	1.161***	0.029	1.116***	0.016	1.053***	0.017	0.958***	0.019
2015	1.238***	0.025	1.141***	0.018	1.124***	0.018	1.025***	0.015
Full sample	1.160***	0.159	1.099***	0.126	1.016***	0.133	0.949***	0.142
Full sample#	1.303***	0.288	1.164***	0.112	1.060***	0.107	0.963***	0.138

*Note: *** significant at the 1% level.*
Scale elasticities are estimated through equation (3.9), Full sample# is the estimation of equation (3.9) through function (3.3) parameterised for non-TBTF banks in the sample. All values are estimated at the mean of the data.
The t test is performed for SE estimates with the null hypothesis that the mean equals one.
See Table 3.17 for the classification of asset size groups.

Source: Author's own calculations

Table 3.19: Estimated scale inefficiencies in each asset size group.

Year	**Asset group 1**	Std. error	**Asset group 2**	Std. error	**Asset group 3**	Std. error	**Asset group 4**	Std. error
2005	21.89%	1.259	32.87%	8.299	17.89%	2.171	11.91%	3.615
2006	21.62%	3.899	17.95%	9.508	6.41%	1.609	9.17%	5.685
2007	29.33%	15.962	9.17%	1.990	3.59%	1.294	2.72%	1.571
2008	19.00%	5.554	10.79%	3.129	3.40%	2.725	2.59%	1.141
2009	4.17%	1.328	1.49%	0.442	1.73%	0.839	4.66%	0.958
2010	9.58%	4.843	1.71%	0.741	1.66%	0.547	5.16%	1.035
2011	3.71%	1.987	1.54%	0.395	1.65%	0.485	4.15%	0.944
2012	5.88%	3.412	1.27%	0.280	2.16%	0.644	4.38%	1.070
2013	2.86%	0.882	1.70%	0.315	1.28%	0.454	3.36%	0.911
2014	6.56%	1.693	3.28%	0.579	1.66%	0.477	2.07%	0.831
2015	11.62%	2.650	4.45%	0.626	3.65%	0.855	1.06%	0.612
Full sample	8.70%	13.684	4.16%	7.134	2.85%	5.207	3.65%	5.672

The Table presents the estimation results of equation (3.17).
See Table 3.17 for the classification of asset size groups.

Source: Author's own calculations

Table 3.20: Estimates of THC and TSB across sub-sample categories.

	THC	Std. error	TSB	Std. error
Asset group 1	-0.025	0.393	0.001	0.082
Asset group 2	0.005***	0.141	0.007*	0.081
Asset group 3	0.023***	0.073	0.008*	0.081
Asset group 4	-0.042***	0.205	0.011***	0.080
Full sample	-0.010	0.008	0.007	0.081

*Note: *** significant at the 1% level, ** significant at 5%, * significant at 10%.*
THC refers to the estimation results of technological change for sample banks based on equation (3.20),
TSB denotes the estimates of scale-biased technological change for banks by equation (3.21).
THC and TSB estimates are multiplied by -1.
The t test is performed for THC and TSB estimates with the null hypothesis that the mean equals zero.
See Table 3.17 for the classification of asset size groups.

Source: Author's own calculations

Table 3.21: Estimates of THC and TSB over the sample period.

	THC	Std. error	TSB	Std. error
2005	-0.086	0.506	-0.175***	0.005
2006	-0.086	0.408	-0.145***	0.005
2007	-0.128***	0.346	-0.119***	0.005
2008	-0.155***	0.277	-0.091***	0.006
2009	-0.100***	0.213	-0.061***	0.006
2010	-0.059***	0.103	-0.031***	0.006
2011	-0.021***	0.077	-0.003***	0.006
2012	0.012*	0.091	0.027***	0.005
2013	0.041***	0.143	0.056***	0.005
2014	0.068***	0.204	0.087***	0.005
2015	0.076***	0.283	0.118***	0.006

*Note: *** significant at the 1% level, ** significant at 5%, * significant at 10%.*
THC refers to the estimation results of technological change for sample banks based on equation (3.20),
TSB denotes the estimates of scale-biased technological change for banks by equation (3.21).
THC and TSB estimates are multiplied by -1.
The t test is performed for THC and TSB estimates with the null hypothesis that the mean equals zero.

Source: Author's own calculations

3.5.4 Results by Bank Clusters

Ghossoub and Reed (2015) point out that size alone is not an adequate indicator of bank funding and investment strategies. Earlier empirical research by Brown and Glennon (2000) supports the weakness of size as the sole grouping standard. Those authors divided sample banks into six groups with regard to asset size and quantile regression showed that many banks with a similar portfolio mix were assigned to different size groups. Furthermore, the absolute values of dispersion towards the median value reflected that each size class consisted of a relatively heterogeneous (in terms of product mix) group of banks. Consequently, tested banks' portfolio composition is not captured by size alone, suggesting that asset size might not be a suitable categorising criterion for banking estimation.

A more precise categorising approach which focuses directly on bank balance sheet composition is proposed in our study – the clustering analysis is used as the appropriate segmentation method to define natural clusters (groups) of observations on the basis of bank product mix. It should be mentioned that bank product mix consists of various classifications of assets, liabilities, and off-balance sheet behaviours, and aggregating these activities as collections of variables can make it difficult to analyse the resulting groups (Kapetanios, 2006). However, clustering analysis is able to identify groups in data, to define natural clusters (i.e., segmentations) of observation (Amini, Rezaeenour and Hadavandi, 2015). It is an exploratory method of data analysis that is able to process large amounts of data based on pre-determined similarity or dis-similarity measures; furthermore, it is computationally efficient.

Of the different types of cluster analysis, the K-means and hierarchical methods are the two most advanced and most commonly used techniques within econometric studies (Kaushik and Mathur, 2014). The K-means is a partition approach. It starts by determining the number of groups, K, to create using an iterative procedure. Then, data are allocated to the cluster whose mean is closest and the average values for new groups are defined in terms of this categorisation. The process continues until there are no data (observation) changes clusters. In this way, the algorithm starts with an initial value of K that performs as K cluster mean (Herrera-Restrepo *et al.*, 2016).

Kaushik and Mathur (2014) show that the hierarchical cluster method produces hierarchically related groups of clusters in either an agglomerative or a divisive way. The agglomerative process starts with the assumption that each entity is regarded as one distinct cluster, that is, N clusters, each of size one. Next, the two closest clusters will merge, resulting in N-1 clusters, with one of size two and all the remainder of size one. These steps are repeated until all observations are assigned to the same cluster. Clearly, this method creates a hierarchy of clusters.

The divisive method is the inverse of the agglomerative technique. It begins with the assumption that all observations are within one big cluster, then divides them until all entities are grouped into specific clusters. Our study follows Brown and Glennon (2000), and the divisive approach to hierarchical cluster analysis is employed to group sample banks into a predetermined number of disjoint clusters using a minimum distance criterion. Different clusters are constructed via the analysis of all possible pair-wise comparisons of composition of a bank's balance sheet to that of composition of the mean portfolio of each cluster[111]. A sample bank will be appointed to the cluster in which the composition of its portfolio most closely resembles that of the cluster's mean portfolio. Then, after clustering, the Calinski and Harabasz pseudo-F index is generated to check the stopping rules for the cluster analysis. Gordon (1999) and Everitt et al. (2011) advise that the stopping rules are applied to determine the number of clusters in the dataset – higher values of the Calinski and Harabasz pseudo-F index imply a more distinct clustering. As a result, in our study, all banks are assigned to four distinct clusters since the four-group solution generates the highest value of Calinski and Harabasz pseudo-F index (3662.29). To have a more intuitive comparison of each peer group, Table 3.22 presents the mean percentage of assets in each chosen banking activity across four clusters. Our assumption that the Chinese banking system

[111] Following Brown and Glennon (2000), the similarity measure utilised in our cluster analysis to allocate sample banks to specific clusters is the composition of a bank's portfolio, including the accounts of real estate loans, corporate and commercial loans, consumer loans, securities, customer deposits, short-term borrowing and off-balance sheet items. However, the consumer loans account was dropped since more than 75% of sample banks display missing values for this account.

is appropriately segmented by product mix seems to be justified by the observed variation in average values across clusters. The distribution of banks within clusters by asset size group is shown in Table 3.23.

Banks within the cluster 1 are large, since they were all assigned to the highest asset quartile group. Over 60% of their assets are represented by securities (24.59%) and corporate and commercial loans (38.3%). They hold the highest portion of securities and real estate loans (9.55%) among all clusters. Their assets are primarily funded with customer deposits (78.98%) and they have few off-balance sheet liabilities. Interestingly, banks that are allocated to this cluster are the Big Four. The banks in cluster 2 are predominately bigger in asset size as more than 80% have total assets above CNY131,080.5 million. A considerable proportion of their assets are funded by short-term borrowing – the highest percentage (21.05%) among all groups. In addition to offering a full range of traditional banking services, they are also heavily involved in off-balance sheet activities. These banks are located in urban areas and about two-thirds of them are joint-stock commercial banks.

Around 77% of sample banks are in cluster 3, and they are more evenly distributed within clusters across size categories with asset group 4 has the least number of banks. This indicates that the majority of Chinese banks have similar investment and funding strategies, with little involvement in real estate, corporate and commercial loans, but, rather, more focus on traditional banking services, and with limited off-balance sheet exposures. In addition, they are proportionately distributed between developed and rural areas. The product mix of banks assigned in cluster 4 shows that, on average, these banks rely less on customer deposits. They tend to specialise in off-balance sheet services (which are a significant portion of their on-balance sheet assets). Moreover, these banks are large in terms of asset size and over half are state-owned commercial banks.

That the accuracy of any clustering technique needs to be examined. Here, the stability of cluster membership over the period 2014 to 2015 is employed as an illustration. Table 3.24 shows that majority of sample banks remain in the same cluster over 2014-2015; indeed, only 3 banks switch, from cluster 3 to cluster 2 in 2015. Cluster 1 and cluster 4 contain the same sample banks in both years. Overall, the proportion of banks that stay in the same clusters are high, demonstrating the robustness of the clustering approach.

Table 3.22: Mean ratios of chosen measures to total assets, by clusters.

	Securities	Real estate loans	Corporate and commercial loans	Customer deposits	Short-term borrowing	Off-balance sheet items
Cluster 1	**0.2459**	**0.0955**	0.3830	**0.7898**	0.1005	0.1416
Cluster 2	0.2190	0.0540	0.3841	0.6731	**0.2105**	0.2158
Cluster 3	0.2300	0.0251	0.3386	0.6704	0.1864	0.1666
Cluster 4	0.2035	0.0565	**0.3881**	0.6254	0.1719	**0.2466**

Where the chosen measures are the eight bank accounts that specified in the first row of this Table.

Source: Author’s own calculations

Table 3.23:Distribution of sample banks within clusters by asset groups.

	Asset group 1	Asset group 2	Asset group 3	Asset group 4	Whole sample
Cluster 1				100%	4.35%
Cluster 2			13.24%	86.76%	9.24%
Cluster 3	22.12%	33.10%	33.63%	11.15%	76.77%
Cluster 4				100%	9.64%

Source: Author’s own calculations

Table 3.24: Stability of membership in clusters (2014-2015, as % of 2015 banks).

		2014				
	Clusters		1	2	3	4
	Number of banks		4	5	89	10
2015	1	4	4			
			100%			
	2	8		5	3	
				62.5%	37.5%	
	3	77			77	
					100%	
	4	10				10
						100%

Source: Author's own calculations

Having discussed above the estimation results based on four size groups, we now break down the estimates of scale economies, scale inefficiency and technological change by bank clusters – see Table 3.25, 3.26 and 3.27, Figure 3.12 and 3.13 – and address the interpretations of our findings across each cluster. As shown in Figure 3.12, in terms of estimated scale elasticities, our sample overall tends to skew towards SE taking a value of less than one. For instance, more than 90% of banks in cluster 1 are operating under increasing returns to scale, and this cluster as a whole generates a mean of elasticity of 0.858. That is, for the given production technology, and similar asset and liability composition, the Big Four on average are able to save on operating costs by extending their production scale or through consolidation[112].

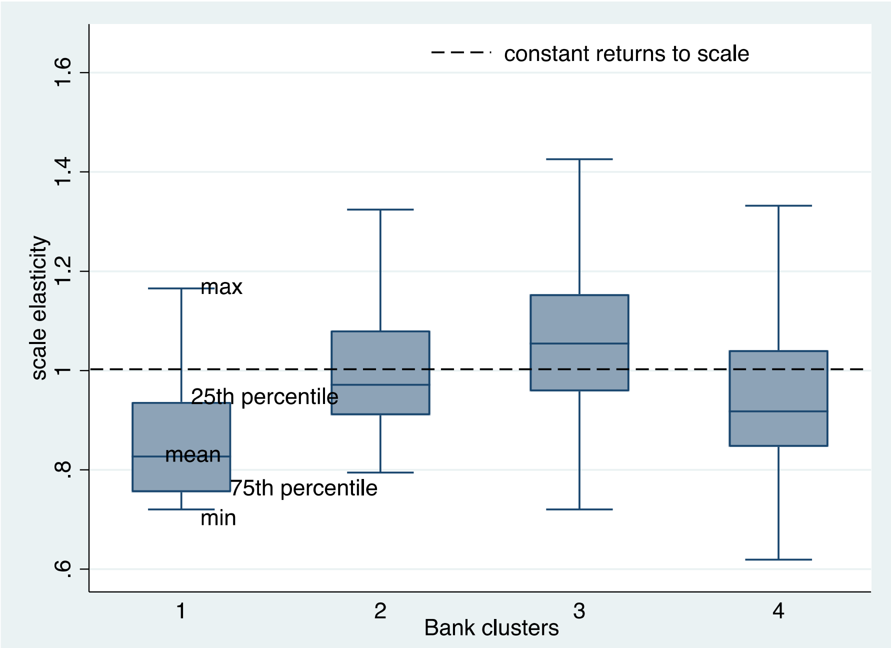
With respect to banks in cluster 4, a mean of scale economies of 0.979 is observed. Compared with the Big Four (cluster 1), over half the banks in cluster 4 are the large state-owned commercial banks that specialise in off-balance sheet operations and their assets are funded more by short-term borrowing. This suggests that these largest banks within cluster 1 and 4 – all banks are classified into the asset quartile with the highest (fourth quartile) individual assets value (see Table 3.23) – take advantage of globalisation to realise greater economies of scale by allowing them to pursue cheaper

[112] As do their European peers, Huang, Lin and Chen (2017) argue that employing consolidation for large Chinese banks can be effective in the view of improving their current weak profitability performance.

resources around the world. These banks are able to enjoy scale economies because the liquidity risk of deposits as well as credit risk of loans and other financial services are better diversified. This efficiently lowers relative costs of managing these risks and raises opportunities for them to conserve their liquid assets and, more importantly, their equity capital (Beccalli, Anolli and Borello, 2015).

Our findings are in accordance with what has been reported by Hou, Wang and Li (2014), whose paper identifies the product-specific scale economies for Chinese banks. Their results demonstrate that banks with business models more oriented to investment banking are able to achieve greater scale economies. Our study reaches a similar conclusion by showing that more economies of scale arise for largest state-owned banks (in cluster 1), which are oriented toward security operations, with stable Tier 1 capital and better liquidity. According to our estimation, other than downsizing the banks, policy makers and bank regulators could focus on reducing TBTF subsidies through better resolution and contingent capital requirements, since limiting bank size will induce economic costs for them in the form of forgone scale economies. Hung et al. (2017) further argue that the Big Four as market monopolists are normally less inclined to reduce their costs by downsizing. More importantly, they will face major challenges if they reduce their lending for social and political purposes.

Figure 3.12: Scale elasticity estimates in each bank cluster.



Scale elasticity is estimated through equation (3.9) and see Table 3.22 for the identification of bank clusters.

Source: Author's own calculations

Banks in cluster 2, on average, exhibit constant returns to scale, indicating that medium-large and large Chinese joint-stock banks[113] that are reliant on short-term funding are operating at the optimum scale in terms of their product mix. In general, to the literature suggests that more relaxed regulations allow stronger financial innovation, and that the mature operations of joint-stock banks enable them to more efficiently spread costs over their outputs (see Matthews, 2013 and Dong et al., 2016).

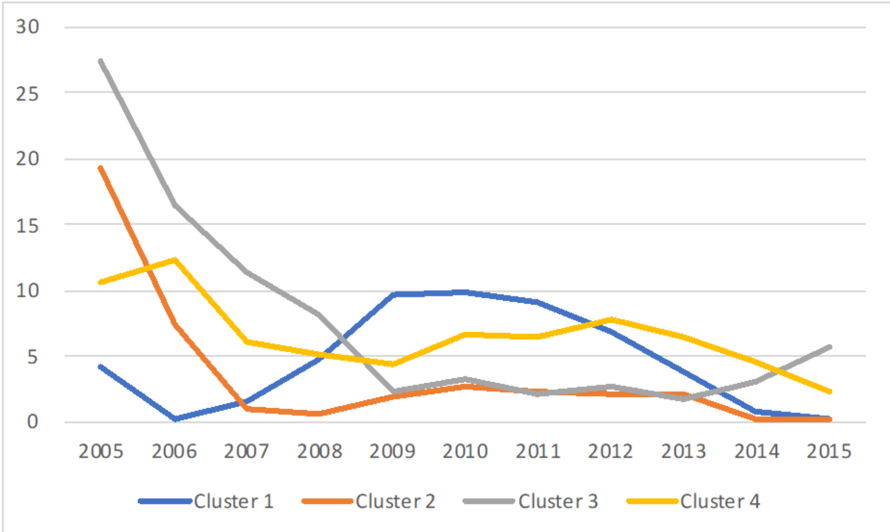
The portfolios of banks in cluster 3 are close to the industry average – a third of assets in corporate and commercial loans and a quarter in securities. These banks' assets are mainly funded by customer deposits, but also short-term borrowing (see Table 3.22). Table 3.23 shows that these banks are more evenly distributed across asset size groups.

[113] All banks grouped into cluster 2 are the medium-large and large Chinese joint-stock banks (see Table 3.23), with only one exemption – Bank of Beijing – a medium-large Chinese city commercial bank.

Overall, they offer a full range of traditional banking services in proportion to industry norms. Equation (3.9) yields a mean of scale elasticity of 1.063 for cluster 3, that is, minor diseconomies of scale are witnessed for these banks. It should be noted that after the GFC, increasing returns to scale were presented for the majority of Chinese banks during 2009 to 2011 (see Table 3.25). As Hou, Wang and Li (2014) suggest, the first wave of public interventions in the Chinese banking system during the crisis period involved numerous take-overs of insolvent banks by large healthy ones, which offered opportunities for banks to exploit scale economies in the following years. Table 3.26 shows the scale efficiency of banks in clusters 2, 3 and 4 improved substantially over 2005 to 2007. Within this time period, banks in those clusters were more motivated or compelled by competitive pressure to employ advanced technical and managerial skills to minimise disproportionate cost growth in relation to increases in their outputs.

Figure 3.13 presents an interesting difference in the scale inefficiency patterns across each bank cluster. On average, cluster 4 exhibits the highest level of scale inefficiency, followed by clusters 1 and 3, while banks in cluster 2 had the best practice from a scale perspective. Such findings are basically in line with what has been observed and discussed above regarding the scale performance of sample banks in each banking cluster. Focusing on banks in cluster 3, the estimates of cost inefficiencies are broken down into 4 groups by asset quartiles. We find a mean of scale inefficiency of 8.71% for banks that are classified into the asset quartile with the lowest (first quartile) asset value. Means of 4.16%, 2.34% and 1.52% are found for the second, third and fourth quartiles, respectively. Our results suggest that smaller banks, with similar investment and funding strategies, were crippled by heavy regulation during the study period. That is, due to intense government control, smaller banks was their earnings fall, their costs go up and their ability to make small business and consumer loans curtailed (Laeven, Ratnovski and Tong, 2016).

Figure 3.13: Scale inefficiency estimates in each bank cluster.



Scale inefficiency is estimated through equation (3.17) and see Table 3.22 for the identification of bank clusters.

Source: Author's own calculations

With respect to the estimates of technological change for representative banks in each cluster, banks in clusters 1 and 4 (mainly state-owned commercial banks) are found to experience substantial technical regress over the examined period (see Table 3.27). Meanwhile, banks in cluster 2 and cluster 3, as well as the whole sample, display no technological advancement. As for the scale-biased estimates (TSB), only cluster 3 produces a significant estimate of scale-increasing technological change (1%). In contrast, a scale-decreasing technological change (-2.4%) is experienced by banks in cluster 2, implying that these banks (mainly national joint-stock commercial banks) are actually in favour of fragmentation (Tadesse, 2006).

Table 3.25: Estimated scale elasticities in each bank cluster.

Year	**Bank cluster 1**	Std. error	**Bank cluster 2**	Std. error	**Bank cluster 3**	Std. error	**Bank cluster 4**	Std. error
2005	1.166***	0.019	1.338***	0.019	1.385***	0.040	1.253***	0.037
2006	1.039***	0.021	1.210***	0.025	1.295***	0.037	1.202***	0.098
2007	0.897***	0.026	1.059***	0.022	1.217***	0.028	1.080***	0.100
2008	0.824***	0.017	0.987***	0.034	1.141***	0.027	0.956***	0.079
2009	0.757***	0.024	0.934***	0.042	1.009***	0.019	0.948***	0.080
2010	0.755***	0.024	0.880***	0.024	0.988***	0.019	0.939***	0.098
2011	0.763***	0.020	0.892***	0.025	0.988***	0.014	0.935***	0.086
2012	0.795***	0.019	0.897***	0.027	1.003***	0.014	0.883***	0.066
2013	0.846***	0.018	0.899***	0.027	1.023***	0.012	0.906***	0.062
2014	0.934***	0.019	0.958***	0.007	1.083***	0.012	0.958***	0.054
2015	1.030***	0.020	1.022***	0.012	1.154***	0.013	1.018***	0.041
Full sample	0.858***	0.120	1.010***	0.150	1.063***	0.148	0.979***	0.193

*Note: *** significant at the 1% level.*
Scale elasticities are estimated through equation (3.9). All values are estimated at the mean of the data.
The t test is performed for SE estimates with the null hypothesis that the mean equals one.
See Table 3.22 for the identification of bank clusters.

Source: Author's own calculations

Table 3.26: Estimated scale inefficiencies in each bank cluster.

Year	**Bank cluster 1**	Std. error	**Bank cluster 2**	Std. error	**Bank cluster 3**	Std. error	**Bank cluster 4**	Std. error
2005	4.24%	1.185	19.25%	2.091	27.42%	6.491	10.69%	3.407
2006	0.23%	1.462	7.44%	1.490	16.52%	3.980	12.36%	10.104
2007	1.63%	1.248	1.05%	0.362	11.37%	3.895	6.11%	5.566
2008	4.83%	1.963	0.71%	0.285	8.23%	1.981	5.26%	2.737
2009	9.69%	1.748	2.02%	0.937	2.30%	0.467	4.48%	1.757
2010	9.83%	1.779	2.65%	0.934	3.37%	1.074	6.70%	2.803
2011	9.14%	1.473	2.28%	0.915	2.09%	0.487	6.58%	3.079
2012	6.80%	1.198	2.19%	0.869	2.69%	0.868	7.91%	2.953
2013	3.83%	0.867	2.13%	0.781	1.72%	0.264	6.45%	2.578
2014	0.83%	0.426	0.31%	0.103	3.18%	0.476	4.53%	2.591
2015	0.31%	0.135	0.23%	0.085	5.84%	0.892	2.42%	1.671
Full sample	5.39%	4.342	3.58%	5.701	4.26%	8.459	6.08%	8.269

The Table presents the estimation results of equation (3.17).
See Table 3.22 for the identification of bank clusters.

Source: Author’s own calculations

Table 3.27: Estimates of THC and TSB across sub-sample categories.

	THC	Std. error	TSB	Std. error
Bank cluster 1	-0.182***	0.328	0.014**	0.079
Bank cluster 2	0.016	0.120	-0.024	0.096
Bank cluster 3	0.001	0.227	0.010**	0.078
Bank cluster 4	-0.068**	0.257	0.003***	0.089
Full sample	-0.010	0.008	0.007	0.081

*Note: *** significant at the 1% level, ** significant at 5%, * significant at 10%.*
THC refers to the estimation results of technological change for sample banks based on equation (3.20),
TSB denotes the estimates of scale-biased technological change for banks by equation (3.21).
THC and TSB estimates are multiplied by -1.
The t test is performed for THC and TSB estimates with the null hypothesis that the mean equals zero.
See Table 3.22 for the identification of bank clusters.

Source: Author's own calculations

3.6 Empirical Results of Determinants of Economies of Scale

A summary of empirical findings of determinants of economies of scale in the Chinese banking based on regressions (3.23) and (3.24) is provided in this section. We first discuss the results of pre- and post-estimation diagnostics performed for our dynamic GMM estimators, then proceed to the interpretation of model results (see Table 3.28). As shown, the results of ordinary least squares (OLS) and fixed effects (FE) estimation of the baseline specification (3.23) are offered in Table 3.28, for comparison. Where the Breusch-Pagan test shows a p value of 0.000 (see column A of Table 3.28), the null hypothesis that the error variances are all equal can be rejected. This means heteroskedasticity exists and OLS estimates are no longer BLUE. In this scenario, FE estimates are preferred because they take account of unobserved heterogeneity across panels. Indeed, groupwise heteroskedasticity is demonstrated for the FE[114] model by the p value (0.000) of the modified Wald test (see column B of Table 3.28).

Nevertheless, as a type of static model, FE regression assumes that the probability of

[114] The Hausman test rejects the null at the 1% significance level with a p value of 0.000 and the fixed effects model is hence chosen over the random effects model.

moving (or staying) in or out of a state is not correlated with the occurrence or past non-occurrence, whereas time persistence is a common occurrence in banking models and the majority of previous empirical studies therefore adopted dynamic panel models for their estimation (e.g., Athanasoglou, Brissimis and Delis, 2008; Lee and Hsieh, 2013; Chronopoulos et al., 2015; and Fang et al., 2019). The rationale for us to propose a dynamic panel data model – where SE_{it-1} is included in model specifications (3.23) and (3.24) – are given in section 3.4.2. It should be noted that FE regression will suffer a severe bias (commonly known as the Nickell bias) in a dynamic panel data model. '*As Nickell (1981) shows, this arises because the demeaning process which subtracts the individual's mean value of y and each x from the respective variable creates a correlation between regressor and error*' (Wooldridge, 2013, page 489).

That is, since SE_{it-1} is correlated with the mean of v_{it} through the term of v_{it-1}, it leads to a biased estimate of the coefficient of SE_{it-1} in the FE regression. Such a bias cannot be mitigated by increasing the number of observations (banks) as the demeaning process is generating a regressor that is not independently distributed from the error component. To account for this endogeneity feature of SE_{it-1}, as discussed, the system GMM estimator is employed in this chapter for the estimation of equations (3.23) and (3.24). The empirical findings under the GMM technique are displayed in column C-D of Table 3.28. A comparison of the parameter estimates in columns A, B and C of Table 3.28 shows that all lagged components are highly significant across each of the modelling approaches.

Specifically, the OLS estimator yields a coefficient value of 0.739 for the lagged dependent variable, and a value of 0.527 is found under the FE model. The GMM estimator produces a coefficient value of 0.568 with respect to SE_{it-1}. It is well known that there tends to be an upward bias in the estimate of coefficient on SE_{it-1} in the context of OLS regression, as SE_{it-1} is generally positively correlated with u_i (see Arellano and Bond, 1991). In contrast, the FE estimate of the coefficient on SE_{it-1} tends to be biased downward (Blundell and Bond, 1998). In our case, the magnitude of the coefficient for SE_{it-1} estimated utilising FE is lower than that estimated by OLS. As expected, the coefficient for SE_{it-1} estimated using system GMM offers a reasonable result, given the GMM estimate is higher than the FE estimate (lower limit) and lower than the OLS estimate (upper limit).

Table 3.28 (columns C and D) shows that both the baseline equation (3.23) and the extended equation (3.24) satisfy all estimation diagnostics discussed in section 3.4.2. In detail, the number of instruments used (63/82) in the estimation is smaller than the number of groups (118/118) observed in the sample dataset for the function (3.23)/(3.24), indicating that models are free from instrument proliferation. The view that the IVs utilised are valid (i.e., exogenously determined and not correlated with function error term) is supported by the Hansen-J-statistic: a value of 0.269 is found for equation (3.23) and a value of 0.348 for equation (3.24). In addition, the Difference-in-Hansen test (0.530/0.572) justifies our treatment of instrumentalising the lagged term by its own first lag. Furthermore, the yielded statistic (0.684/0.555) of the Difference-in-Hansen test for levels equation suggests the validity of subsets of IVs used in levels equation during estimation. Then the results of AR (1) and AR (2) demonstrate that there are no serial correlation problems for either function.

Overall, our baseline regression (3.23) reveals a few interesting results with regard to the impacts of diversification in the business model and risk-taking characteristics on the realisation of scale economies in Chinese banking. First, the significant sign obtained for lagged dependent variable SE_{it-1} justifies our presumption regarding the dynamic nature of panel model specification and the persistence of cost economies. That is, economies of scale in Chinese banking do not follow a random walk, and the lagged term imposes positive effects on the current level of cost economies. This suggests that greater economies of scale are seen for those sample banks that exhibited stronger competency to exploit scale economies over the previous year. A coefficient value of 0.568 (see column C of Table 3.28) indicates that economies of scale persist at a moderate level. Yet, it will finally return to the average level – a value of the coefficient that approaches 0 indicates a high speed of adjustment, whereas a value close to 1 means a low speed of adjustment (Athanasoglou, Brissimis and Delis, 2008).

Second, SEC_{it} is found to be positively associated with the increase in the magnitude of scale economies, meaning that larger economies of scale are obtained if banks' business models are more oriented toward investment banking activities. This finding is in line with what has been reported by Beccalli, Anolli and Borello (2015). In view of the policy debate on 'too big to fail', employing a panel dataset that consists of 103 European listed banks, they examine evidence of scale economies for large European banks over the period 2000 to 2011. Their empirical findings demonstrate that a primarily investment bank could benefit most from scale economies, even during the crisis period. However, in the present study this association is not significant (with a p value of 0.102; see column C of Table 3.28). Similarly, the non-significant coefficient in $SFTF_{it}$ indicates that the utilisation of short-term wholesale funds does not determine the differences across Chinese banks in terms of economies of scale.

Third, LR_{it} appears to increase cost economies, as indicated by a statistically significant coefficient with a value of -1.186 (see column C of Table 3.28). We observe that greater scale economies are experienced by sample banks that have higher liquidity or banks that are subject to lower liquidity risk; this would support the conclusion that tightened Basel III liquidity rules (e.g., liquidity coverage ratio and net stable funding ratio[115]) increase the chances for Chinese banks to exploit economies of scale. This result is supported by Hou, Wang and Li (2014). Based on the estimation of Chinese commercial banks, Hou, Wang and Li (2014) find that banks with higher liquidity are in a better position to develop future operations and hence have more opportunity to realise scale economies. Several earlier studies, including Hughes and Mester (2013) and Berger and Bouwman (2015), also document a positive association

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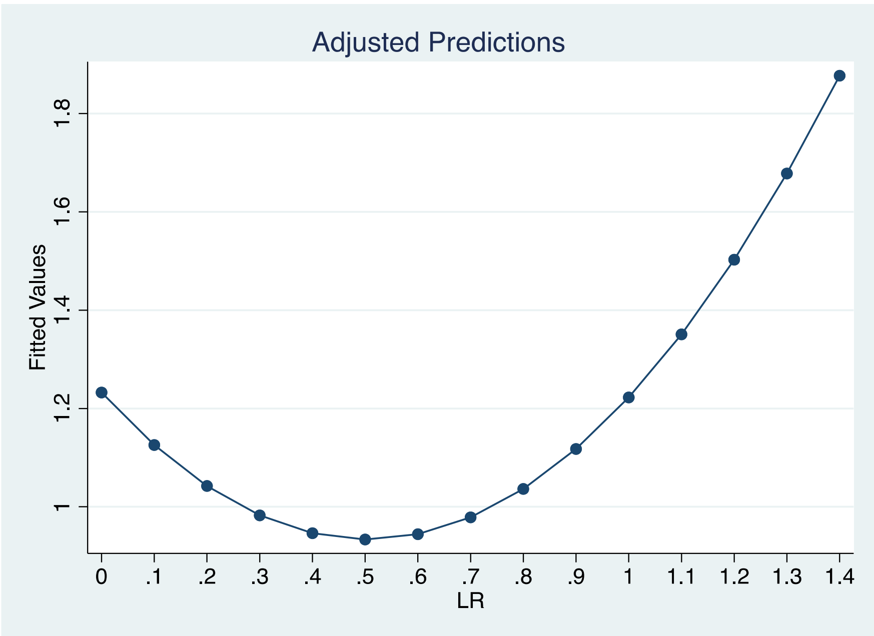
[115] According to BIS (2013b), the liquidity coverage ratio (LCR) is designed to improve banks' short-term resilience on their liquidity risk profiles by requiring them to hold an adequate stock of high-quality liquid assets to survive a severe adverse scenario that lasts for 30 days. BIS (2013b) proposes that the minimum requirement level of LCR for G-SIBs is 60% on 1 January 2015; this target was set to increase by 10% every year since then, and banks were to reach a minimum of 100% by 1 January 2019. Net stable funding ratio (NSFR) promotes banks to establish a more sustainable maturity structure on their balance sheet in two ways: (i) a longer funding tenor creates more incentives for banks to employ longer-term capital to fund their assets, as these liabilities are considered to be more stable than short-term liabilities; and (ii) encouraging banks to obtain funding from more stable counterparties such as retail customers and small business customers, since deposits offered by these sources are assumed to be behaviourally more reliable than the wholesale funding of the same maturity from other resources (BIS, 2014).

between bank liquidity and cost economies.

To further explore the consequence of liquidity risk on scale economies, the quadratic term of the liquidity ratio is discussed. $LRsq_{it}$ has a positive coefficient (1.176; see column C of Table 3.28), which signifies a parabola shape for its margin plot (see Figure 3.14). Indeed, this convexity indicates that the positive correlation between liquidity and scale economies holds only for sample banks whose liquidity ratio is below 58.47%[116]. When the ratio exceeds this threshold, the increase in bank liquidity decreases cost economies. This adverse effect means that above certain levels, liquidity becomes an indicator of managerial inefficiency and/or lack of business investment decisions that limit positive cost-efficiency externalities, resulting in a net social loss.

Figure 3.14: Margins plot of liquidity ratio of sample banks.



LR: liquidity ratio, measured as liquid assets to deposits and short-term funding.

Source: Author's own estimations

[116] This value is calculated as -$\beta_3/2\beta_4$, as defined in equation (3.23). The 95% confidence interval is [0.238, 0.932].

Fourth, Table 3.28 (column C) shows that a significantly positive correlation (0.342) is recorded between scale economies and the values of LLP_{it}, arguing that credit risk-taking behaviours reduce the magnitude of economies of scale generated by sample Chinese banks. In general, banks with high credit risk will require more loss reserves, which may reduce cost economies due to the increased marginal costs of risk management (Badunenko and Kumbhakar, 2017). On the whole, concerning the effects of risk-taking features on scale economies, our empirical findings suggest that better liquidity and credit risk management allows Chinese banks to exploit more economies of scale over the study period. Finally, $T1_{it}$ yields a positive but non-significant coefficient, indicating that cost economies seem to be irrelevant with bank's capital strength.

As was mentioned in section 3.4.2, to examine the significance of TBTF, the extended model (3.24) is used. With respect to $TBTF_i$, our result is in accordance with Beccalli, Anolli and Borello (2015), whereas a significantly negative relationship (-0.339) is seen between the TBTF status and economies of scale (see column D of Table 3.28). This implies that greater cost economies can be realised for 15 TBTF banks in China. For Chinese D-SIBs (the TBTF dummy variable taking the value of 1), the value of the coefficient on $T1_{it}$ (-0.257) and the coefficient on the interaction term $T1_{it} * TBTF_i$ (2.699) reveal the effects of $T1_{it}$ on scale economies for these banks. The aggregate value of 2.442 indicates that holding higher levels of regulatory capital actually reduces cost economies, particularly for TBTF banks, as these banks face higher compliance-related costs than non-TBTF institutions.

Interestingly, when the dummy variable and interaction term are considered, equation (3.24) shows that the influence of $T1_{it}$ on scale economies depends on the TBTF status of sample banks – tightened Basel III capital requirements adversely affect scale economies for TBTF banks while boosting the levels of economies of scale for non-TBTF banks. Similar to the conclusion drawn by us in above section 3.5.2, again, our analysis of determinants of economies of scale suggests that the need to break up TBTF banks does not seem to be justified for our Chinese sample. Moreover, given what the world banking sector experienced during the GFC, Zedda and Cannas (2017) point out that regulatory authorities have heaped unprecedented attention upon the banking industry with the aim to ensure the stability of the financial system. Nevertheless, there is increasing debate regarding the costs of numerous regulations implemented during the last decade, and the main concern is that the regulatory burden is not only applying high compliance costs[117] on large financial institutions (as demonstrated by our findings relating to the TBTF in regression 3.24), but is also inhibiting innovation[118] (e.g., Pasiouras, Tanna and Zopounidis, 2009; Bongini and Nieri, 2014; Schmaltz et al., 2014; and Buchak et al., 2018). This serves as a reminder to policy makers that they should balance the need for safety of the financial system with the need to promote financial innovation and dynamism when they formulate regulations for banking.

Indeed, the above examination is conducted by incorporating $TBTF_i$ dummy variable and its interaction term with $T1_{it}$ into baseline regression (3.23) for estimation. The rationale for us to employ this dummy variable instead of the variable of yearly systemic importance scores/rankings to inspect the significance of 'too big to fail' in our scale economies determinants analysis is detailly specified in section 3.4.2. Here, to take a step further, we include the yearly systemic importance scores[119] into regression (3.23) for estimation to investigate whether the empirical results yielded from this estimation are similar to those obtained when $TBTF_i$ is chosen for estimation. The empirical

[117] To illustrate, Schorr (2019) has quantified and investigated the potential effect of the G-SIB capital buffer on JP Morgan Chase and Bank of America. To calculate the additional cost of the 'capital buffer' (see Table 3.2), Schorr compares the incremental Basel III Tier 1 capital cost for these two systemically important banks relative to the cumulative capital cost if they were split into smaller entities (thus avoiding the G-SIB charge). Based on the empirical analysis, he points out that the incremental Basel III Tier 1 common capital required for JP Morgan Chase and Bank of America would be US$24 billion on a combined basis versus that of an equivalent non-G-SIB bank.

[118] In this regard, the UK the 2013 Financial Services Act, the Switzerland 2011 TBTF Banking Act, the United States Dodd-Frank Act, the European Union proposal on the structural reform of banks. Specifically, in January 2014 the European Commission proposed a structural reform aimed at minimising the risky activities of the EU's 30 systemically important banks (European Commission, 2014). Starting in 2017, the proposal bans proprietary trading for banks that are labelled by international regulators as TBTF in the global economy, or whose activities surpass certain financial thresholds.

[119] As shown in Table 3.5, the data of yearly systemic importance scores is only available for the 15 TBTF sample banks. Accordingly, the 120 non-TBTF sample banks will be confronted with missing values issue with respect to this variable during estimation. To address this, we assign a value of 0 to this variable for all non-TBTF sample banks during estimation. Whereas TBTF sample banks will take the actual value of yearly systemic importance scores (as specified in Table 3.5) in estimation.

findings produced when yearly systemic importance scores are added are displayed in Table 7.6 in Appendix A. A comparison of the parameter estimates in Table 7.6 (column D) and Table 3.28 (column D) shows that these two sets of results are broadly similar[120].[121] In this circumstance, $TBTF_i$ is chosen over yearly systemic importance scores in examining the significance of TBTF since utilising $TBTF_i$ would be more in line with the purpose of our analysis (see related discussions on page 111) and the estimation of its interaction term with $T1_{it}$ enriches our study by giving information on whether capital strength imposes different impacts on the realisation of economies of scale for TBTF banks and non-TBTF banks.

[120] Specifically, the empirical results when $TBTF_i$ and its interaction term with $T1_{it}$ are included into baseline regression (3.23) for estimation are presented in column D of Table 3.28. Then, instead of $TBTF_i$, we incorporate the variable of yearly systemic importance scores and its interaction term with $T1_{it}$ into equation (3.23) for estimation. Its empirical findings are displayed in column D of Table 7.6 (in Appendix A). By comparing these two sets of results, we find that each of the same variables yields two similar parameter estimates (excluding the parameter estimates on $T1_{it}$) that show the same sign and are both statistically significant/insignificant. The model results exhibited in columns A, B and C of Table 7.6 are identical to those displayed in columns A, B and C of Table 3.28, as the three same models are estimated (see the footnote below each table that explains the estimation models for each column of model results).

[121] Besides, this demonstrates the robustness of our proposed model estimation – parameter estimates provide valid information for our scale economies determinants study of Chinese banks.

Table 3.28: Empirical findings for equation (3.23).

Explanatory variables	OLS – equation (3.23)	FE – equation (3.23)	GMM – equation (3.23)	GMM – equation (3.24)
	A	**B**	**C**	**D**
SE_{it-1}	0.739***	0.522***	0.568***	0.602***
	(0.023)	(0.028)	(0.067)	(0.042)
SEC_{it}	-0.102***	-0.076	-0.075	-0.003
	(0.032)	(0.050)	(0.102)	(0.076)
$SFTF_{it}$	0.128**	-0.135*	-0.235	-0.007
	(0.062)	(0.077)	(0.357)	(0.248)
LR_{it}	-0.419***	-0.663***	-1.186***	-0.684***
	(0.088)	(0.119)	(0.447)	(0.165)
$LRsq_{it}$	0.514***	0.632***	1.176**	0.636***
	(0.128)	(0.175)	(0.592)	(0.206)
LLP_{it}	0.147***	0.117***	0.342**	0.267***
	(0.026)	(0.029)	(0.147)	(0.046)
$T1_{it}$	0.054	0.068	0.280	-0.257*
	(0.062)	(0.140)	(0.397)	(0.188)
$TBTF_i$				-0.339**
				(0.143)
$T1_{it} * TBTF_i$				2.699*
				(1.385)
_cons	0.328***	0.553***	0.633***	0.541***
	(0.032)	(0.039)	(0.102)	(0.058)
R-sq (overall):	0.753	0.709		
Breusch-Pagan	0.000			
Modified Wald test		0.000		
Number of IVs (groups)			63(118)	82(118)

Hansen-J-statistics			0.269	0.348
Difference-in-Hansen test (SE_{it-1})			0.530	0.572
Difference-in-Hansen test for levels equation			0.684	0.555
AR (1)			0.008	0.003
AR (2)			0.847	0.535

**Correlation is statistically significantly different from zero at the 10% level, **Correlation is statistically significantly different from zero at the 5% level, ***Correlation is statistically significantly different from zero at the 1% level. Standard errors are in parenthesis.*

SE_{it-1}: the autoregressive term, SEC_{it}: the securities to total assets ratio (%); $SFTF_{it}$: the short-term funding to total funding ratio (%); LR_{it}: the liquid assets to total customer deposits ratio (%); $LRsq_{it}$: the quadratic term of LR_{it}, LLP_{it}: the loan loss provision to total loans ratio (%), $T1_{it}$: the Tier 1 regulatory capital ratio (measured as the Tier 1 capital minus regulatory deductions as a percentage of bank risk-weighted assets), $TBTF_i$: the dummy variable that takes the value of 1 for the domestic systemically important banks and 0 for the remaining banks, and $T1_{it} * TBTF_i$: the interaction term of $T1_{it}$ and $TBTF_i$.

Column A shows the estimation result of the dynamic base model as in equation (3.23) through the ordinary least squares (OLS) approach, column B is the estimation result of the dynamic base model as in equation (3.23) through the fixed effects approach, column C presents the estimation result of the dynamic base model as in equation (3.23) through a two-step System Generalised Method of Moments approach, column D is the estimation result of the dynamic base model as in equation (3.23) through a two-step System Generalised Method of Moments approach by adding on the TBTF dummy variable and its interaction term with the Tier 1 regulatory capital ratio.

R-sq represents the R squared value (overall) to show the fitness of the OLS and FE estimation, Hansen-J-statistics tests the joint validity of all instrumental variables included, Difference-in-Hansen test confirms the validity of specified subsets instruments, AR (1) and AR (2) are the Arellano-Bond test for checking the assumption of no autocorrelation in error terms.

3.7 Conclusion

The scale analysis of the Chinese banking system examines whether industry consolidation is a rational aim for larger Chinese banks, given they are deemed to be too big to fail. This chapter links the examination of scale economies with scale efficiency to explore size benefits and/or costs amongst Chinese banks. Compared with previous related banking studies, our research takes a different view by splitting the full sample and analysing banks across asset groups (i.e., quartile measures) and also employing a clustering technique to further decompose the sample banks into group on the basis of product mix. A rationale for asset groupings is that it is difficult, if not impossible, to gain information on actual outputs of banks across different asset size.

Overall, we find minor diseconomies of scale for the whole sample across the tested period, and these diseconomies are mainly attributed to financial inefficiency, such overpayment of interest, rather than operational inefficiency, such as the overuse of physical capital and labour. However, substantial scale economies are observed for banks that are allocated to the quartile (asset group 4) with the highest assets value. More importantly, our study estimates the cost function (equation 3.3) parameterised for non-TBTF sample banks and finds that cost savings enjoyed by those largest Chinese banks indeed represent scale economies rather than TBTF subsidies. The policy proposition of limiting the size of financial institutions, under these circumstances, may cause competitive disadvantage for big Chinese banks in the form of forgone scale economies. Instead of downsizing, TBTF subsidies could be mitigated through better resolution and contingent capital requirements.

Banks whose assets are in the range CNY49,590.346 million to CNY131,022.17 million are best able to minimise costs. Accordingly, these banks (in asset group 3) exhibit the highest rate of scale efficiency across the 4 size groups. To the author's best knowledge, our study is the first to utilise the Li test to empirically examine the distributional equality of efficiency estimates across different model specifications when the specified risk variables are included separately or in different combinations in the efficiency estimations. The best fitted model is Model 5 (when all three risk factors are considered). By incorporating risk factors in the cost function (3.3), we show that ignoring risk considerations results in biased efficiency estimates for banks in the sense that the inclusion of financial risk costs notably decreases the level of scale efficiency for Chinese banks.

In addition, our research is the first empirical study (to the best of our knowledge) to partition sample Chinese banks into groups in terms of investment and funding strategies – through clustering analysis – to address the concern that size alone might be an insufficient categorising standard. We observe that banks in cluster 1 (the Big Four) experience substantially increased returns to scale, and a larger extent of scale economies is attained by banks in cluster 4 (mainly state-owned banks) through expansion of off-balance sheet operations. Returning briefly to the above case, the higher scale efficiencies mainly originate from off-balance sheet banking activities, with banks displaying higher Tier 1 capital ratio and stable liquidity. Cost savings that arise from off-balance sheet operations suggest that deregulation and diversification do indeed contribute to the development of Chinese banks and should be incorporated in the policy agenda for the subsequent marketisation reforms of the Chinese banking industry.

Average Chinese banks (cluster 3) present slightly diminishing returns to scale, while joint-stock banks that are reliant on short-term funding (cluster 2) operate with constant returns to scale. With regard to the estimates of technological change, there is evidence to suggest an underlying technical progress has increased the comparative advantages of large-scale operations in the Chinese banking sector. The scope of economies of scale has been rising over time and estimates of scale-biased technological change imply an increase in the minimum size of a bank for it to be efficient. Hence, the technological progress that has been shaping the Chinese market offers justification for bank consolidation and concentration. As for the determinants of economies of scale, greater cost economies are experienced by banks with higher liquidity, lower credit risk and TBTF status.

Having analysed the scale economies and scale efficiency of the Chinese banking system, in the chapter that follows, we will focus on the evaluation of profitability and insolvency of the sample Chinese banks.

Chapter 4

An Evaluation of the Performance of Chinese Banks: An Analysis of the Determinants of Bank Profitability and Stability

4.1 Chapter Summary

This chapter adds to the Chinese banking literature by offering more recent findings with respect to the cost efficiency, profitability and financial stability of Chinese banks. It is a warranted and timely evaluation in the context of the ongoing recapitalisation and banking transformation in China. Indeed, over the past few decades, Chinese banks have encountered a sequence of unprecedented structural changes, and substantial banking reforms are in progress as a response to the recent banking crises. The operations and business models of banks have changed substantially due to the rapidly evolving operating environment in the banking market. Therefore, it is of particular interest to examine the potential effects of such changes on the performance (i.e., profitability and stability) of banks for managers, regulators and policy makers. On the one hand, this kind of analysis can strengthen bank managers' managerial decisions and improve the competitive advantages of the Chinese banking sector within the international market. On the other hand, it offers empirical evidence that sheds the light on policy.

This chapter is structured as follows: section 4.2 provides an introduction and section 4.3 reviews recent bank profitability and stability studies. Then section 4.4 explains the methods used for the estimations in the present study, including model specifications, the variables, data collection and summary statistics. Section 4.5 presents a detailed analysis of the empirical findings and section 4.6 concludes.

4.2 Introduction

In 1978, the Chinese government initiated a series of banking transformations,[122] with the intention of enhancing the performance and competitive conditions of banks and ensuring the stability of the industry (Dong, Girardone and Kuo, 2017, also see Table 2.1 for a summary of the major banking reforms that Chinese banks have undergone over the last four decades). This has been accompanied by globalisation and the opening up of the banking market. Among these financial reforms, in order to diminish financial risks and enhance bank solvency, the Chinese central government has implemented aggressive recapitalisation programmes since 1998 (Ariff and Can, 2008). Indeed, as explained in section 2.6, one long-standing obstacle that has hampered Chinese banks is the undercapitalisation of the banking sector. The Chinese government has worked hard to restore the capital base of Chinese banks. For instance, over the period 1998 to 2005, utilising foreign exchange reserves and borrowing from the Ministry of Finance, Chinese authorities completed a CNY769.6 billion capital injection plan for its 'Big Four'[123]. Chinese banks are also encouraged to acquire fresh capital through listing on stock exchanges (see Table 2.4)[124].

Moreover, with the aim of attracting foreign investments, the Chinese government has further opened its banking market by allowing foreign investors to hold up to 25% of the ownership of domestic banks. As a result, during 2004 to 2008, 24 Chinese banks raised new capital from 36 foreign partners (García-Herrero, Gavilá and Santabárbara, 2009). In addition, the capital position of Chinese banks is further strengthened with the full formal participation of Chinese banks in the Basel capital criteria (Basel II capital rules took effect in China from 2004 and were replaced by the tighter Basel III capital

[122] See the detailed discussions of these banking transformations in section 2.3.

[123] To recap, the Big Four are the four largest state-owned banks in the Chinese banking system – Industrial and Commercial Bank of China (ICBC), Bank of China (BOC), China Construction Bank (CCB) and Agricultural Bank of China (ABOC). The aggregated assets of these four banks accounted for roughly 46% of China's total banking assets in 2018 (Fang et al., 2019).

[124] In total, 23 Chinese banks had listed on the Shanghai, Shenzhen or Hong Kong Stock Exchange by the end of 2015. Among them, 18 banks initiated Initial Public Offerings (IPOs) over our sample period of 2005 to 2015.

rules from 2013). Following the Basel capital requirements, the China Banking Regulatory Commission (CBRC) issued a series of capital rules (see Table 2.5) to update the previous relaxed domestic regulations in order to boost the quantity and quality of the core capital of banks. All these programmes have increased the stability of the Chinese banking system. However, the recapitalisation places resource costs on banks, and its effects on bank performance are thus of interest to bank managers and supervisory authorities.

By estimating the shadow return on equity (shadow price of equity) utilising a bank cost function, Fethi, Shaban and Weyman-Jones (2012) and Boucinha, Ribeiro and Weyman-Jones (2012) investigated the cost of recapitalisation on Turkish and Portuguese banks, respectively. Following their framework, we examine this significant issue within the context of the Chinese banking industry. Specifically, our study develops a stochastic frontier cost specification subject to a capitalisation constraint to estimate the shadow return on equity. To the best of our knowledge, only one published banking paper – Dong et al. (2016) – empirically explores this issue focusing on Chinese banks, covering the period 2002 to 2011. Our study enriches the empirical evidence on this topic with more recent Chinese data.

It is reasonable to presume that all the above reforms impose great challenges to Chinese banks as the environment in which banks operate has changed substantially and rapidly. One of the most prominent challenges is that the financial deregulation and liberalisation have damaged the profitability of Chinese banks (Xu, van Rixtel and van Leuvensteijn, 2016 and Hou et al., 2018). Indeed, as explained in section 2.5, recently, Chinese banks have witnessed significant reductions in their earning abilities (see Figure 2.9). This raises concerns for bank managers and regulators, given that a profitable and sustainable banking industry is crucial in maintaining the stability of the financial system and sustaining the nation's economic growth[125] (García-Herrero,

[125] China is a typical bank-based economy, in that bank credits constitute more than half of the annual new credit supply (e.g., bank loans represented nearly 60% of total credit supply in 2017) (Wu, Song and Chai, 2018). Therefore, the profitability of banks is of particular significance to China's economic development.

Gavilá and Santabárbara, 2009). Accordingly, this chapter attempts to identify what underlying factors lead to low profitability within the Chinese banking sector. The yielded estimation results in turn offer valuable information for managers to strengthen banks' profit-generating ability. The comprehension of such contributing factors also offers insights to other developing countries whose banking sectors are undergoing significant institutional and structural change.

Besides, the Chinese banking sector's high contribution to GDP[126] suggests the risk of over-leveraging. Namely, the Chinese banking industry is getting bigger and critical. Hence, our study comes in time for the market and policy makers to enable an examination of the fundamental factors that affect banks' capacity to cope with adverse shocks in the financial system (or the economy), with the aim of maintaining the stability of the Chinese banking system. It is worth emphasising that Chinese banks play a special role in the Chinese financial system. As a group, they have a virtual monopoly on financial intermediation in China.[127] Across 2002 to 2017, every year, on average, about 50%-87% of corporate funding in China was provided by bank loans (Werner and Chung, 2010 and Wu, Song and Chai, 2018). Consequently, ensuring the stability of the banking system is crucial for maintaining the well-functioning of China's real economy.

Overall, this chapter extents prior studies on the estimation of determinants of bank

[126] The ratio of bank assets to GDP was equal to 110.69% in 2006 and reached a high of 174.54% in 2016, see Figure 2.4.

[127] In this regard, as Werner and Chung (2010) point out *"the history of commercial banking in China is only about 25 years old, while its banking system relative to other more developed countries is immature, financial markets are even more immature. The equity markets, nearly two decades old, are volatile as they lack a stabilising diversified institutional investor base. The fixed-income market (both exchange-traded and over-the-counter) is dominated by government issuance as the corporate debt market is hampered by weak secondary liquidity and an untested bankruptcy law"* (Page 13). That is, Chinese financial markets (e.g., stock markets and bond markets) are volatile due to the great uncertainty about the quantity of tradable shares since the majority shares of listed companies are generally owned by government and outside investors fear that if prices go up then the government will sell its holdings and thereby prevent further increases in prices or even depress them. Werner and Chung (2010) further suggest that another immature feature of the Chinese financial market is the lack of diversified financial products other than stocks (e.g., lack of corporate bonds and derivative securities). Thus, the underdevelopment of the Chinese financial market has resulted in the monopoly status of the banking sector in its financial system.

profitability and stability in Chinese banking to investigate to what extent bank performance in China is affected by a series of factors in view of the ongoing financial transformations in China. More specifically, our analysis highlights four aspects of the banking industry in China. First, our research studies the effects of bank cost efficiency on profitability and financial stability. That is, in the first stage, following Battese and Coelli (1995), cost efficiency scores are estimated based on the proposed stochastic frontier cost function for banks operating in China. Then, in the second stage, cost efficiency estimates are incorporated as one of the determinants into the bank profitability and stability regression models. In the banking literature, numerous studies have included cost-related accounting ratios (e.g., cost to income ratio or operating costs to total assets ratio) in their estimations to explore the impacts of operating efficiency on bank profitability and stability (see Pasiouras and Kosmidou, 2007; Dietrich and Wanzenried, 2011; Fu, Lin and Molyneux, 2014; Khan, Scheule and Wu, 2017 and Rahman et al., 2017). Nevertheless, despite their popularity and regardless of their use, ratios are not without limitations and have numerous shortcomings discussed in the literature.

DeYoung (1997, page 21) points out that "*myopic analysis of expenditures can be misleading – reduced spending on labour, materials, or physical plant is no guarantee that a bank is being run efficiently, and high levels of spending on these items do not necessarily signal inefficiency*". In terms of accounting ratios, an illustration of such a misspecification is the cost to income ratio, which can increase as intensified competition lowers bank interest margins or when a bank is confronted with higher personnel expenses. In this vein, the cost to income ratio produces biased efficiency values and consequently leads to inconsistent estimators in the second stage regressions.

In a further step, this chapter constructs stochastic frontier cost efficiency scores to be included in the second stage regressions to examine potential correlations among bank efficiency, profitability and stability. The notion that cost efficiency scores are better efficiency indicators than the commonly utilised accounting ratios is based on the fact that this efficiency measure takes into account information on the composition of multiple input prices and outputs. Accounting ratios do not readily allow the analysis of a mix of bank inputs and outputs, and are more applicable in a single input-output case, as ratios provide information on factor-specific performance (Thanassoulis, Boussofiane and Dyson, 1996). For example, the frontier cost function takes into account synchronously all aspects of bank performance, and can show a bank to be operating well even when individual financial performance indicators suggest the bank is inefficient (Berger, Hasan and Zhou, 2009). Meanwhile, estimating cost efficiency through cost frontier construction enables us to investigate the influences of environmental (exogenous) variables on the cost function in a direct manner during the first stage of efficiency estimation.

Second, the banking reforms, the experience of the global financial crisis (GFC) and the post-crisis market environment have had marked effects on Chinese banks. In response to their new operating environment, Chinese banks have been adjusting their business models and strategies. As indicated previously in section 2.7, two such underlying changes are the shifting of bank assets towards shadow banking activities and the increasing reliance of Chinese banks on short-term wholesale funding. The involvement of banks in shadow banking operations and the utilisation of short-term wholesale funding could generate profit gains but with excessive risk taking. For a more detailed analysis on the potential gains and risks associated with shadow banking activities and wholesale funds, see section 2.7. Indeed, such risky banking operations could be a significant source of systemic risk, exposes banks to liquidity and credit risk and renders the economy very sensitive to unexpected adverse shocks, thereby drawing regulators' concern. During the GFC, the most devastating runs were not on bank deposits but on shadow banking exposures such as mortgage-backed securities (Du, Li and Wang, 2017). The burst of these exposures rapidly drained up banks' capital holdings and sharply reduced (later froze) the liquidity flow in the financial system.

However, surprisingly, very few studies have inspected the effects of shadow banking activities on the performance of banks in China. One such study is that by Ding, Fung and Jia (2015). Their study constructs a bank cost function to explore the impacts of shadow banking on the cost efficiency of Chinese banks over the period 2005 to 2013. Focusing on Chinese commercial banks for the years of 2003-2014, Hou et al. (2018) examine whether the association between shadow banking operations and bank cost efficiency changes across heterogeneous categories of government political intervention. Wu and Shen (2019) investigate whether the risks from shadow banking transactions can be mitigated by good corporate governance by examining Chinese banks over the period 2010-2016. There is also one theoretical paper – Li and Lin (2016) review bank interest revenues when the bank participates in both shadow banking activities and traditional lending under capital requirements. To the best of our knowledge, there are no published empirical studies on Chinese banking that pay attention to the effects of shadow banking activities on bank profits and soundness. Therefore, our study fills this research gap by associating variation in bank profitability and stability with variation in shadow banking activities.

Similarly, there are very few studies analysing the potential effects of short-term wholesale funding on Chinese banks' profitability and stability. Nanto and Sinha (2002) performed a theoretical review of the possible influences of wholesale funds on the performance of Chinese banks. Qi and Yang (2017) examined empirically how the presence of foreign banks and short-term wholesale funding affected Chinese banks' interest margins over the period 2000-2009. Thus, our study extends the literature on the determinants of profitability and stability in the Chinese banking sector by estimating the impacts of short-term wholesale funding with more recent data.

Third, as explained earlier in section 3.3.2, severe negative externalities can arise from the failures of banks that are deemed to be 'too big to fail' (i.e., systematically important banks). To recap briefly, the distress of banks that are too big to fail (TBTF) can rapidly spread systemic risk throughout financial markets and into the real economy. The financial, economic and social costs of government bailouts of such banks have been enormous. Consequently, new banking initiatives such as the Basel III regulations enforce constraints on large banks in the form of more capital and liquidity and also to restrain riskier areas of operation – all of which curb banks' size. There is in fact an on-going policy debate on the possible application of a size cap on large banking institutions, that is, on whether a maximum size of bank should be a confirmed policy measure to ensure system stability. As such, the examination of the size-stability nexus will provide evidence for current regulatory discussions of downsizing in banking.

In light of such policy debate, this chapter first estimates the correlation between bank asset size and bank stability, to see whether bank fragility increases with size. We then split the full sample into two groups, TBTF banks and non-TBTF banks, in order to test whether the TBTF status of banks increases system instability. The effects of asset size and the TBTF status on bank profitability is also inspected to check if explicit size restrictions would cause banks to lose any profit gains that would arise from greater bank size. Contributing to the current Chinese banking literature, the findings from the above proposed estimations shed the light on the policy choice for banking authorities.

Fourth, our study offers a comprehensive account of the effects of the macroeconomic environment on the profitability and stability of the Chinese banking industry. Two sets of macroeconomic variables are introduced in estimation which allow us to perform a thorough investigation of the extent to which the profitability and stability of Chinese banks are driven by the domestic and international macroeconomic settings.

4.3 Theoretical Background

4.3.1 Literature Review of Bank Profitability

Empirical papers on bank profitability primarily pay attention to banks in the European, US and Asian economies. The studies undertaken have either placed emphasis on the evaluation of the internal and external determinants of bank profit of an individual country or focused on cross-country analysis (see, for instance, Molyneux and Thornton, 1992; Demirgüç-Kunt and Huizinga, 2000; Iannotta, Nocera and Sironi, 2007; Kling, Paul and Gonis, 2014; and Sayari and Shamki, 2016). That is, in the literature, bank profitability is normally deemed to be determined by a combination of internal and external factors. The internal factors are bank-specific variables (e.g., capital) that reflect the managerial skill of a bank, whereas the external factors concern systemic impacts on the performance of a bank related to the legal environment (e.g., Basel III regulations), economic environment (e.g., inflation) and market characteristics (e.g., concentration) (Athanasoglou, Brissimis and Delis, 2008).

With respect to internal determinants, empirical studies examine micro variables such as cost management, non-performing loans, capital and size. Extensive studies have incorporated cost-related variables in profitability analysis and commonly find that banks with higher management efficiency tend to enjoy higher profits. For instance, Pasiouras and Kosmidou (2007) adopt the cost to income ratio to estimate the effects of management efficiency on profitability for 584 European commercial banks for the years 1995 to 2001. They suggest that a higher ratio implies banks are sluggish to manage and control their expenses and thus are confronted with higher costs and so lower profits. Similarly, Athanasoglou, Brissimis and Delis (2008) point out that poor cost management was among the main contributors to the low profitability of Greek commercial banks during 1985-2001. Their paper views operating costs as the outcome of bank management, whereby lower operating expenses indicate greater management efficiency. More efficient banks in the Greek sample enjoyed higher earning capacity as they were in a better position to allocate and utilise loanable resources to generate incomes. However, using cost efficiency scores as a proxy for management efficiency, Rahman et al. (2017) show that greater levels of cost efficiency reduce bank interest earnings[128]. This may be attributed to banks passing on the benefits from cost savings to borrowers by charging lower margins on loans to increase their market share.

The positive relationship between bank costs and profitability can also be explained from the perspective of efficiency wage theory. For example, both Dietrich and

[128] Rahman et al. (2017) analyse the impacts of cost efficiency on bank capital and profitability based on a sample of 1,190 banks from BRICS countries (i.e., India, South Africa, Brazil, China, Russia) over the period 2007–2015.

Wanzenried (2011) and Mirzaei, Moore and Liu (2013)[129] utilise overhead costs as the efficiency measure and argue that the high operating costs may derive from high wages paid to staff. They believe higher wages can substantially boost staff productivity and hence improve bank returns. Accordingly, if the resultant increase in earnings is larger than the extra sums paid in wages, profitability will be increased.

The variable of non-performing loan (NPL) is commonly employed as an indicator of asset quality and is widely considered to have significant impacts on bank profitability (Louzis, Vouldis and Metaxas, 2012). Miller and Noulas (1997) propose that NPLs reduce bank interest revenues and capital base through the required provisioning of doubtful loans and write-off of unpaid loans. Moreover, high levels of NPLs may indicate a relaxed credit approval process and weak corporate governance in banks. In response, banks need to put more effort into improving their credit risk management practices, and therefore are confronted with additional operating costs and, ultimately, decreased profitability (Berger and DeYoung, 1997). Bikker and Hu (2002) empirically confirm these profit-reducing effects of NPLs on a panel dataset of international banks from 26 industrial economies over the period 1979-1999. Similarly, focusing on Italian banks over the period 1993-2003, Chiorazzo, Milani and Salvini (2008) also find NPLs adversely affect bank profitability and further argue that high levels of NPLs can incur extra regulatory costs to sample banks for their high-risk assets.

Lee and Hsieh (2013) analyse the profitability of 2,276 banks in 42 Asian economies over 1994-2008. They hold the view that the higher the volumes of NPLs, the poorer is the credit quality. Hence, banks with excessively high stocks of NPLs will face higher financing costs due to their lower credit ratings, which adversely affects both their equity valuations and their profits. Zhang et al. (2016) employ a sample of 87 Chinese commercial banks to evaluate the influences of NPLs on bank behaviours in China from 2006 to 2012. According to the estimation results, a significantly negative correlation is observed between the NPL ratio and earnings. The higher the NPL ratio, the higher

[129] Dietrich and Wanzenried (2011) evaluate the profitability of 3,72 Swiss commercial banks for the years of 1999 to 2009, whereas Mirzaei, Moore and Liu (2013) analyse the effects of market structure on profitability for 1,929 banks from 40 industrial and developing countries during the period 1999 to 2008.

is the probability that more loan loss will be charged against earnings. Similarly, Ahamed (2017) and Partovi and Matousek (2019) provide evidence of such a negative relation for a sample of Indian commercial banks in 1998-2014 and a sample of Turkish bank in 2002-2017, respectively.

Bank capital strength is also considered to be one of the important determinants of profitability. Berger (1995) suggests the existence of a positive relationship between capitalisation and profitability for US commercial banks during 1983-1989. He hypothesises that higher capitalisation signals higher creditworthiness in the market, which in turn improves bank earnings through lowered funding costs. Several recent studies, including Iannotta, Nocera and Sironi (2007), García-Herrero, Gavilá and Santabárbara (2009) and Fu, Lin and Molyneux (2016), also find evidence for this for banks in 15 European countries, China and 14 Asia Pacific countries, respectively. García-Herrero, Gavilá and Santabárbara (2009) suggest that another reason to believe that holding higher levels of capital enhances bank profitability in China is that a well-capitalised bank needs to borrow less in order to support a given level of assets. They point out this is particularly significant for banks in emerging economies, where banks' ability to borrow is more subject to sudden stops.

In contrast, employing a dataset of US banks over 1996-2013, Tran, Lin and Nguyen (2016) document a negative association between capitalisation and bank incomes. Their empirical findings show that, taking corporate tax into consideration, holding more capital decreases debt financing, and banks' after-tax income is reduced due to the decline in tax-shield effects. Similarly, focusing on Chinese commercial banks during the period 2003-2013, Tan, Floros and Anchor (2017) indicate that lower levels of profitability are seen for Chinese banks with better capital positions. They suggest that the more capital, the safer is the bank, and therefore managers in better capitalised banks are encouraged to undertake riskier businesses that weakens banks' income margin through increased financing costs. Berger and Bouwman (2013) provide empirical evidence of such a negative relation for US banks in 1984-2010 and Beltratti and Paladino (2016) for European banks in 2007-2011.

The variable of size is introduced as a crucial profitability determinant to capture information on economies or diseconomies of scale in the market (Bikker and Hu, 2002). The empirical research has yielded mixed results on the correlation between size and profitability. On the one hand, several studies, including Goddard, Molyneux and Wilson (2004) and Loukoianova (2008), suggest that banks with more assets are more diversified in terms of business models, funding resources and operation segments, and therefore are more profitable than smaller banks[130]. Based on an examination of 123 Chinese commercial banks from 1996 to 2002, Shih, Zhang and Liu (2007) find that greater size allows banks to generate cost savings from economies of scale, which in turn boosts profitability. On the other hand, Athanasoglou, Brissimis and Delis (2008) show that earnings initially improve with size but then decrease when further increases in assets result in diseconomies of scale. Employing a sample of Greek banks over the period 1985-2001, their paper offers empirical evidence of this non-liner correlation between size and profitability. Moreover, Varotto and Zhao (2018) argue that there is a negative association between size and profit among ‘too big to fail’ European and US banks from 2004 to 2012, as their income-generating capacity is depressed by high compliance costs (the costs related to the fulfilment of additional regulatory requirements imposed by authorities because of their enormous size).

Moving on to the external determinants of profitability, it should be noted that Athanasoglou, Brissimis and Delis (2008) categorise these into two groups: macroeconomic control variables, such as economic growth, inflation and interest rates; and industry-specific variables that represent market characteristics, such as stock market development. Economic growth and inflation are included to control for potential cyclical movements in bank profitability, and have long been considered in empirical analyses. For instance, utilising the annual GDP growth rate as the indicator of economic growth, Chan and Karim (2010) find evidence of a positive relation between economic growth and the earnings of commercial banks from 43 developing

[130] Goddard, Molyneux and Wilson (2004) study the dynamics of firm growth and profitability utilising a sample of 625 savings, commercial, and co-operative banks from seven European economies covering the period 1993 to 1998. Loukoianova (2008) examines the efficiency and profitability of Japanese banks during the period 2000 to 2006.

economies in Asia and the Middle East over the period 2000-2005. The authors conclude that economies "*with a higher per capita income have a more mature banking system that translates to more competitive interest rates and profit margin*" (Chan and Karim, 2010, page 277).

García-Herrero, Gavilá, and Santabárbara (2009) obtained a similar result in their examination of the impacts of GDP growth on bank profitability in China over the period 1997 to 2004. They point out that economic development affects the demand and supply of bank credit in the market. Normally, during boom periods, there will be high demand for bank lending and with increases in the volume of bank loans Chinese banks' interest margin improves. In contrast, Dietrich and Wanzenried (2011) find that the profitability of Swiss commercial banks is inversely related to economic growth during the period 1999 to 2009. This result is in line with finding reported by Tran, Lin and Nguyen (2016) on the US banking industry over the period 1996-2013. These two studies show that an expansion in the real economy increases bank overhead costs, which in turn reduces profitability. Furthermore, economic growth can lower the entry barrier to the banking market, which may reduce profitability due to the increased competition.

On the question of the effects of inflation on profitability, Perry (1992) suggests that the growth rate of bank earnings will be higher than the growth rate of costs if a bank has the ability to fully anticipate the inflation rate and adjust its interest rate accordingly. This implies that banks' income margins will rise when profits increase quicker than costs. Alternatively, a contrary assumption can be made if banks are not able to anticipate changes in inflation in time. That is, bank may incur losses if unexpected increases in inflation lead to cash flow difficulties for borrowers and so early termination of loan agreements and loan losses. Bikker and Hu (2002) report a negative correlation between inflation and profitability in a dataset of banks in 26 industrial economies over the period 1979-1999. Drawing on 1,334 international banks from 101 economies for the years 1995 to 2007, Demirgüç-Kunt and Huizinga (2010) also find that higher inflation adversely affects profitability. In addition, they posit that a country experiencing high inflation might choose to restrict bank lending credit rationing, which in turn could curb profitability. However, both Lin and Zhang (2009) and Ahamed (2017) observe a positive association between inflation and profitability for Chinese commercial banks in 1997-2004 and for Indian commercial banks in 1998-2014.

Concerning the interest rate, Maudos and De Guevara (2004) analyse European banks over 1993 to 2000 and estimate that a higher interest rate promotes bank profitability through the increased interest spread. This is supported by Iannotta, Nocera and Sironi (2007) looking at the European banking industry over 2000-2009. They propose that higher interest rates are typically associated with greater economic growth because a stronger economy generates higher demand for bank loans, and this increases earning opportunities for banks. Nevertheless, based on a dataset of 3,385 banks in 47 countries over 2005-2013, Claessens, Coleman and Donnelly (2018) suggest that a low interest rate boosts bank earnings because "*low interest rates can help economies recover and enhance banks' balance sheets and performance by leading to capital gains, supporting asset prices and reducing non-performing loans*" (page 1). They estimate that the effects of low interest rates on bank interest income margins are greater than the effects on interest expense margins. Drawing on the Chinese banking sector over the period 1986 to 2008, Li and Zhang (2013) show that the low interest rates encouraged Chinese commercial banks to shift from interest-generating activities to non-traditional banking activities (e.g., wealth management products) and find strong evidence that the expansion of non-traditional banking activities was the main driver of profit growth for Chinese banks during the sample period, especially for joint-stock and city commercial banks.

The last group of profitability determinants are industry-specific variables. For instance, the literature dealing with stock market development in general assumes that a mature stock market benefits bank profitability. Pasiouras and Kosmidou (2007) and Sufian and Habibullah (2010), argue that a well-developed stock market mitigates the risk taking of banks since other funds can be accessed from the market[131]. The

[131] Sufian and Habibullah (2010) conduct an empirical estimation of the effects of economic freedom on

resultant reduced levels of risk allow banks to have better borrowing capacity and thereby enjoy superior levels of profitability. Another possible explanation is proposed by Mirzaei, Moore and Liu (2013), who suggest that a mature stock market lowers the financing costs for banks and enables banks to manage their risk-taking more efficiently as more information on listed firms can be obtained from the market. Moreover, Sayari and Shamki (2016) report that the stock market development had a positive effect on the profitability of Jordanian commercial banks over the period 2009 to 2013. They argue that an efficient capital market reveals more information about firms and hence diminishes moral hazard and adverse selection risks in banking.

Having discussed the possible determinants of bank profitability, an interesting problem is how to select the dependent variable – the indicator of bank profitability – in a profit function. Related empirical studies have employed various indicators for bank profitability. Three commonly used profitability proxies are the net interest margin (Demirgüç-Kunt and Huizinga, 2000; Staikouras and Wood, 2011; and Rahman, Hamid and Khan, 2015), the return on assets ratio (Pasiouras and Kosmidou, 2007 and Kyritsis, Rekleitis and Trivelas, 2015), and the return on equity ratio (Lee and Hsieh, 2013; Lee, Yang and Chang, 2014; and Bitar, Pukthuanthong and Walker, 2018).

The net interest margin (NIM) measures, with respect to all a bank's interest-bearing assets, the spread between interest earnings (from the balance sheet) and interest expenses. It is normally deemed to be a direct proxy for bank profitability as it reflects both banks' ability to earn from intermediation and their competence in managing bank assets and liabilities. However, Fu and Heffernan (2009) note that in order for the NIM to be a valid profitability proxy, interest earnings and expenses should be closely related to bank behaviours, and not to government decisions. This undermines the use of NIM for measuring the profitability of Chinese banks, since the Chinese banking industry has long been functioning as a mechanism for the central government to transfer huge sums to meet its public policy goals. Indeed, García-Herrero, Gavilá and Santabárbara (2009) also raise this point about the Chinese banking system and

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banks' performance on the Malaysian banking system spanning 1999 to2007.

further argue that NIM ignores any profits obtained outside a bank's interest-bearing business and does not take operating costs into consideration. In their study, the return on assets ratio and the return on equity ratio are adopted as profitability proxies for their sample of Chinese banks.

The return on assets (ROA) ratio, expressed as net income divided by total assets, is an indicator of how efficient a bank's management is generating incomes from its assets. The return on equity (ROE) ratio, measured as bank net income as a percentage of total shareholders' equity, is a financial metric of how profitable a bank is in exploiting its equity base. Compared with NIM, both ROA and ROE are more sophisticated profitability indicators because they take into account loan loss provisioning and operational efficiency (Pasiouras and Kosmidou, 2007). Nevertheless, Lin and Zhang (2009) suggest that ROA may be biased in measuring earnings in the Chinese banking industry, because this financial ratio disregards bank off-balance sheet assets, thereby excluding the considerable profits which Chinese banks generate from their off-balance sheet operations[132]. Instead, they utilise ROE to estimate the effects of ownership status on the profitability of Chinese commercial banks over 2000-2012. Their empirical results demonstrate that large state-owned banks, due to policy advantages, are more profitable and more liquid than joint-stock banks. Moreover, state-owned banks with higher liquidity and equity reserves emerge as having a superior level of profit efficiency, followed by those joint-stock banks with higher credit risk and lower overhead costs.

This chapter employs ROE to represent bank profitability; in addition to the limitations of NIM and ROA discussed above, there are further two reasons for this. First, ROE reflects a bank's competitive tactics, operational and risk management capacities, as well as shareholders' behaviours. Second, it directly assesses a bank's ability in managing its equity capital – the most costly type of funding source, with the highest risk premium; its deployment is vital to the success, even the solvency of a bank. However, it should be noted that the accounting value of ROE offers only a rough

[132] Athanasoglou, Brissimis and Delis (2008) also make this point.

measure of bank returns on shareholders' equity because it includes subjective provisions that are expedient to banks' top management at any particular time. That means the calculation of ROE based on the accounting figures in banks' financial statements may produce manipulated values. Accordingly, taking a step further, the shadow return on equity replaces accounting ROE as the bank profitability indicator used in our estimation. As mentioned in section 4.2, the shadow return on equity is calculated as the negative of the elasticity of the bank's total cost relative to the level of equity.

Dong et al. (2016) suggest that *"for a given set of output prices, changes in total costs are the negative of the change in economic profit. Therefore, in the short-run cost function, the negative of the derivative of costs with respect to the fixed level of capital should be considered as the true implicit return on equity"* (page 285). Indeed, the advantage of using the shadow return on equity instead of accounting ROE is that it is computed based on the frontier cost function and hence is more reliable and closer to the true return on equity capital.

4.3.2 Literature Review of Bank Stability

The study of bank stability began very early, long before the collapse of a mass of banking institutions during the GFC, but was rather limited (see, for instance, Cole and Gunther, 1995; De Nicoló, 2000; Wheelock and Wilson, 2000; and DeYoung, 2003). Since the GFC, the solvency of the banking system has become a top priority due to the severe negative externalities of bank failures on national economies, or even the world economy. This has led to great renewed interest from academia and policy makers in evaluating bank stability, with the aim of decreasing the probability of banking failures by ensuring the functioning of any given country's financial system and real economy (e.g., Bushman and Williams, 2012; Kasman and Kasman, 2015; Gofman, 2017; and Ali and Puah, 2019). One of main focuses of such research is to investigate the determinants of bank stability. Generally, researchers have assumed that bank stability is determined by a group of internal factors (bank-specific factors) and external factors (macroeconomic factors).[133]

With respect to bank-specific factors, a group of studies measure the impacts of non-traditional banking activities on bank stability. For instance, examining 47 US bank holding companies over the period 1987-1994, Gallo, Apilado and Kolari (1996) show that an expansion of non-traditional activities generates risk reduction benefits and thereby improves bank solvency. In particular, they posit there are two main sources of such potential risk-reduction effects. First, it is generally believed that asset diversification could reduce bank risk due to the less than perfect correlations between different types of activities. Thus, asset diversification should be capable of stabilising bank earnings by allowing banks to diversify away non-systemic risks. Second, low-risk non-traditional banking activities, such as mutual funds and insurance sales, offer banks an opportunity to hedge systemic risk by shifting assets towards these activities. Smith, Staikouras and Wood (2003) also confirm the risk-reduction hypothesis for a sample of 4,166 banks from 15 European countries over the period 1994-1998. Similarly, Chiorazzo, Milani and Salvini (2008) find that bank securities enhanced the stability of the Italian banking sector during 1993-2003.

In contrast, Zhou and Wang (2008) assume that engaging in non-traditional banking activities has made large banks become very similar to each other, either because bank managers are now more likely to act as a 'herd' by employing business models more like to those of their opponents or because lending, insurance, securities and underwriting operations can take place under the same roof. The resultant decline in intra-industry diversification may give rise to increased systemic risk in the banking system. Accordingly, Zhou and Wang (2008) find that non-interest income reduced the stability of the Chinese banking industry in the period 1999-2006. A similar conclusion has been drawn by De Jonghe (2010). He analyses the effects of non-interest income on bank systemic risk for European bank holding companies over the

[133] The categorisation of bank stability determinants is similar to the categorisation of bank profitability determinants discussed above in section 4.3.1. To recap, internal factors are bank-specific factors that reveal the bank's managerial skill, and external factors are macroeconomic factors that reflect systemic effects on bank behaviours related to the economic environment and market characteristics.

period 1992 to 2007, and concludes that diversification in non-banking activities increases systemic risk and therefore increase instability. Furthermore, in that study, higher levels of systemic risk were observed for banks whose business models moved toward to non-traditional banking activities and, as such, these banks were more vulnerable to severe market conditions than traditional banks. Moreover, DeYoung and Torna (2013) believe that some institutions invest in non-traditional banking activities not in pursuit of profits but to circumvent regulatory requirements.[134,135] Such regulatory arbitrage practices could result in high levels of opaque debt that increase financial risks for banks and undermine their stability.

Another bank-specific variable that has attracted increasing attention is bank funding strategy. A small but growing set of studies has reviewed the effects of diversifying in wholesale funding on bank stability. One such study is that of Huang and Ratnovski (2008). They develop a theoretical model comprehensively analysing the benefits and disbenefits of banks' use of wholesale funds. On the one hand, the non-deposit funding obtained from wholesale capital markets is normally excluded from deposit insurance, but wholesale financiers can perform a monitoring role to discipline banks with poor performance and can refinance good ones. In consequence, wholesale funding is able to lower bank insolvency risk through better monitoring. On the other hand, over-reliance on wholesale funds is found to hinder bank stability. The authors explain this as follows: "*in an environment with a costless but noisy public signal on bank project quality, short-term wholesale financiers have lower incentives to conduct costly monitoring, and instead may withdraw based on negative public signals, triggering inefficient liquidations*" (page 248).

Demirgüç-Kunt and Huizinga (2010), analysing a sample of 1,334 banks across 101

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[134] DeYoung and Torna (2013) thoroughly analyse those US banks that went bankrupt during the GFC and find that asset-based non-traditional banking activities (e.g., investment banking) had greatly contributed to the insolvency of sample banks.

[135] Banks, by utilising regulatory arbitrage, are able to evade minimum regulatory capital requirements, and hence lower their financing costs. This was common practice before the implementation of the Basel III regime, when it was obviously more costly to hold assets with lower levels of risk (Buchak et al., 2018).

economies over 1995-2007, estimate the implications of a short-term funding strategy for bank stability. Their findings suggest that at higher levels of short-term wholesale funding increase a bank's risk profile, while lower levels of short-term wholesale funding offer risk reduction. That is, when the portion of wholesale funds in a bank's funding mix is low, bank risk is reduced through the disciplining effects that comes from financiers. However, when the bank is over-reliant on short-term wholesale funding, this increases the bank's likelihood of facing a potential liquidity crisis if there it suddenly loses its access to wholesale funds in the market. Köhler (2015) links wholesale funding to various types of banks and shows that European investment banks were more stable over the period 2002 to 2006 if they held a higher proportion of non-deposit financing, whereas European retail-oriented banks were less stable if they increased their reliance on non-deposit funding. Vazquez and Federico (2015) provide empirical evidence of the negative correlation between wholesale funding and stability for the US and European banking systems in 2001-2009. In contrast, focusing on US bank holding companies from 1986 to 2014, Khan, Scheule and Wu (2017) find that non-deposit funding reduced bank risk through better capital diversification.

Bank capital strength is also believed to affect bank stability and attracts a large amount of literature. For example, Repullo (2004) proposes that holding higher levels of capital imposes a stabilising effect on banks. That is, higher capitalisation appears to decrease bank risk as it enhances risk monitoring and borrower screening. Repullo emphasises the role of capital as a buffer in absorbing unexpected losses and concludes that well-capitalised banks have a higher loss absorption capacity and hence are more robust to portfolio risk than are thinly capitalised banks. Another possible interpretation backing the view that capitalisation improves bank stability is that greater capitalisation limits moral hazard incentives and gives banks an incentive to invest in less risky assets as well as to strengthen their risk management (Freixas and Rochet, 2008). Such theoretical arguments are supported by the findings of numerous empirical studies, including Nier and Baumann (2006), Zhang et al. (2016) and Anginer, Demirgüç-Kunt and Mare (2018). Utilising a cross-country sample of 728 banks from 32 economies over the period 1993 to 2000, Nier and Baumann (2006) identify that higher capital buffers offset banks' vulnerability to earning shocks, which in turn enhances their financial stability. Zhang et al. (2016) report that greater capitalisation constrained excessive risk-taking for a sample of 87 Chinese banks over 2006-2012 because capital requirements reduce moral hazard by setting a bound on banks' expected return on equity.

Anginer, Demirgüç-Kunt and Mare (2018) investigate the role of capital on bank systemic risk for 1,735 banks from 61 countries for the years 1997 to 2012. Their results demonstrate that bank capital can reduce contagious defaults by offering a buffer to shield against unexpected shocks emerging from the interbank market and by breaking the chain reaction caused by the collapse of individual banks, thus decreasing systemic risk and fostering financial stability. However, on the contrary, several empirical studies, such as Berger and Bouwman (2013) and Duran and Lozano-Vivas (2015), find that higher capital ratios lead to greater fragility in banking. Based on a sample of US banks in 1984-2010, Berger and Bouwman (2013) show that at very high capitalisation levels, a further increase in capital encourages bank risk taking (e.g., well capitalised banks choose risky assets to maximise their returns) as the probability of insolvency is extremely low. Duran and Lozano-Vivas (2015) argue that the cost of lower effort exerted by insiders whose ownership is diluted at higher capitalisation levels is able to offset the risk reduction benefits of capital in decreasing moral hazard. Focusing on 15 European national banking sectors over 2002-2009, those authors find that higher capitalisation decreases bank stability.

In banking stability analysis, the relation between bank size and stability is unclear. On the one hand, Boot and Thakor (2000) and Mirzaei, Moore and Liu (2013) are in favour of the viewpoint that banks with larger assets tend to be more stable than smaller banks. Boot and Thakor (2000) introduce a theoretical model to analyse the behaviours of banks of different size. They hypothesise that the superior franchise value of large banks discourages managers' excessive risk-taking behaviours – and this decline in agency cost offers banks with better investment decisions and improved risk management. Furthermore, according to Mirzaei, Moore and Liu (2013), bigger banks are able to enjoy a better diversified asset structure and associated risks could be reduced through the diversification. Employing a panel dataset of 1,929 banks in 40 countries over 1999-2008, Mirzaei, Moore and Liu (2013) find that size has significantly positive effects on the stability of banks.

On the other hand, Lin and Zhang (2009) and Shleifer and Vishny (2010) report that expansion in size leads to increases in risk. Lin and Zhang (2009) focus on Chinese commercial banks in the period 1997-2004 and show that increase in size reduces bank stability. They explain this negative correlation in terms of moral hazard. That is, large and complex Chinese banks deliberately take on excess risks in the expectation of government bailouts in the event of financial distress since they are too big to fail. This moral hazard hypothesis has also been supported by Zhang et al. (2016) for the Chinese banking system over 2006-2012, as they similarly find strong evidence that systemic risk increases with size.[136] Shleifer and Vishny (2010) propose a theoretical bank operation model and the model predicts that larger banks tend to be more reliant on volatile short-term funds and are more leveraged in risky non-banking activities, which cause them to be more exposed to generalised market failures and liquidity shocks than smaller banks.

Turning to external factors, empirical studies dealing with external determinants adopt macroeconomic variables such as economic growth and inflation. The relation of economic growth to bank stability remains open to question. Intuitively, greater economic growth might be expected to be associated with higher levels of bank stability, since production factors can be more effectively used with higher demand, thereby enhancing managerial efficiency, reducing average costs and ultimately decreasing bank risks (Nier, 2005). Demirgüç-Kunt and Huizinga (2010) offer empirical evidence that high economic growth provides stabilising effects based on a sample of 1,735 banks from 61 countries for the years 1997-2012. Louzis, Vouldis and Metaxas (2012) estimate the impacts of economic growth on bank stability from the view of credit risk for the nine largest Greek banks over 2003-2009 and conclude that stronger economic growth reduces bank credit risk and therefore enhance stability. They argue that during

[136] Large banks tend to be more organisationally complex and have more subsidiaries than small banks, which suggests that they could create more systemic risk.

economic booms, the demand for bank credits grows, which promotes business transactions in the real economy. As a result, business revenue increases, which strengthens the debt-servicing ability of loan borrowers and leads to a reduction in credit risk in banking.

Conversely, Betz et al. (2014) suggest that the stability of the European banking sector significantly decreased between 2000 and 2013, a period of rapid economic growth. One reason could be that intensified competition brought about by economic development prompted banks to take excessive risks. In addition, Soedarmono, Machrouh and Tarazi (2011) and Fu, Lin and Molyneux (2014) discover that banks in emerging Asian economies (e.g., China and Vietnam) tend to be less stable during economic booms.[137] They suggest that banks might loosen their monitoring due to their over-optimistic estimates of borrowers' ability to repay debts in the boom period, which increases the likelihood of bankruptcy if there is an unexpected market failure or financial shock. Amidu and Wolfe (2013) find that this conclusion also applies to banks in other developing countries. Focusing on a cross-country sample of 978 banks from 55 emerging economies (i.e., banks in Africa, Latin America, Eastern and Central Europe and Asia), Amidu and Wolfe (2013) show that such banks become less stable as economic growth increases.

Considering the influences of inflation on bank stability, Boyd, Levine and Smith (2001) put forward the theoretical argument that greater inflation reduces the return on bank assets and thus induces credit rationing and in consequence the exposures of those assets decrease, giving rise to a reduction in credit risk. However, inflation diminishes borrowers' revenues and thus hampers their ability to service previously extended loans, implying an increase in the quantity of non-preforming loans and a raised credit risk. If the risk reduction effects of credit rationing prove to be greater than the effect of non-preforming loans, all else being equal, an increased rate of inflation will boost

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[137] Soedarmono, Machrouh and Tarazi (2011) inspect the linkages between market power, economic growth and financial stability for a panel dataset consisting of banks from 12 Asian economies over 2001-2007. Focusing on commercial banks in 14 Asia Pacific countries in 2003-2010, Fu, Lin and Molyneux (2014) examine the effects of competition on bank stability. Both these empirical studies document a significantly negative correlation between economic growth and stability.

financial stability.

The empirical estimation results regarding the relation between inflation and bank stability have been mixed. For instance, Bohachova (2008) investigates the impacts of inflation on risks in banking according to a large international panel of banks (4,931 banks from 120 countries) over 2001-2005. This paper suggests that the economic uncertainty caused by inflation leads banks to restrict their lending, perhaps to alleviate the adverse selection issues caused by high interest rates. Higher inflation stimulates banks to take fewer risks on their balance sheets and thereby imposes positive effects on bank stability. Contrarily, examining commercial banks from 12 Asian countries for the years 2001 to 2007, Soedarmono, Machrouh and Tarazi (2011) suggest that inflation is negatively correlated with bank stability. They argue a higher inflation rate impairs the quality of existing loan arrangements and thus increases bank insolvency risks. Similarly, Umar and Sun (2018) report a negative association between inflation and stability in the Chinese banking system over the period of 2005 to 2014.

Having analysed potential stability determinants, an issue for the empirical model at hand is to select an appropriate proxy for bank stability. Bank Z-score, proposed by Boyd and Graham (1986), measures a bank's 'distance' to default. It has been widely recognised as a good indicator of financial stability in the empirical literature (e.g., Repullo, 2004; Busch and Kick, 2009; DeYoung and Torna, 2013; Köhler, 2015 and Anginer, Demirgüç-Kunt and Mare, 2018). It is an accounting-based financial ratio, computed as the sum of bank return on assets and capital to assets ratio divided by the standard deviation of return on assets. According to Nier and Baumann (2006), the Z-score links banks' capital level with their income volatility and approximates equity's capacity to absorb variations in incomes before reaching the threshold of insolvency. In this sense, a higher Z-score indicates a lower likelihood of bankruptcy and thus a greater level of stability. Nier and Baumann (2006) use the Z-score as the stability proxy in their empirical research since it explicitly contrasts bank buffers (earnings and capitalisation) with risks (variations in earnings) to illustrate the financial health of tested banks.

Following Nier and Baumann (2006), both Zhou and Wang (2008) and Li and Zhang (2013) utilise the Z-score as the stability indicator in their empirical studies on the Chinese banking system. Li and Zhang (2013) suggest that the Z-score has the further advantage of generating managerial implications. Specifically, the Z-score can be employed by bank managers when integrating business strategy with optimal capital allocation; and its computed values disclose emerging trends in banks' financial condition to their capital and debt holders. Our study also uses the Z-score as the appropriate indicator of financial stability for our sample Chinese banks. In addition to the advantages discussed above, our choice is based on the ability to calculate the Z-score utilising only accounting information. Unlike market-based measures of distance to default, which are calculatable solely for listed banks and which may present estimation concerns originating from the sample size, the Z-score applies to all of our sample banks, listed and unlisted. Overall, as the chosen bank stability measure, the Z-score discloses simultaneously the effects of bank leverage, earnings and the variability in earnings on the financial stability of the Chinese banks examined.

4.4 Empirical Framework

This section moves on from the literature review above to discuss develop the empirical framework for our proposed estimations. First, section 4.4.1 discusses the dynamic panel data regressions used for the analysis of determinants of profitability and financial stability within the Chinese banking industry, as well as the translog cost function utilised for the estimation of cost efficiency and shadow return on equity for sample Chinese banks. Section 4.4.2 presents the data collection for our research and summary statistics of incorporated variables in the estimation.

4.4.1 Model Specification and Variable Description

4.4.1a Determinants of Bank Profitability and Stability

To examine the impacts of the selected variables on profitability and stability of Chinese banks, following Athanasoglou, Brissimis and Delis (2008), a generalised dynamic panel data regression can be expressed as in equation (4.1),

$$
\begin{aligned}
y_{it} = const + \alpha y_{it-1} \\
&+ \beta\{Bank\ specific\ variables_{it} \\
&+ Industry\ specific\ variables_{t} \\
&+ Macroeconomic\ variables_{t}\} + \varepsilon_{it}, \\
&|\alpha| < 1, i = 1, \dots, N, t \dots, T \\
&\varepsilon_{it} = u_i + v_{it}
\end{aligned}
\tag{4.1}
$$

where y_{it} is the profitability/stability of bank i in year t, and $const$ is a constant term. y_{it-1} denotes a one-period lagged term of the dependent variable and α shows the speed of adjustment to equilibrium. The remaining profitability/stability determinants are grouped into three categories – bank-specific, industry-specific and macroeconomic variables. The ε_{it} term contains two parts: u_i represents unobserved panel effects and v_{it} the idiosyncratic error.

Based on equation (4.1), our baseline regressions are defined as follows:

$$
\begin{aligned}
SROE_{it} = const + \alpha SROE_{it-1} + \beta_1 CE_{it} + \beta_2 SHADOW_{it} + \beta_3 SFTF_{it} \\
+ \beta_4 T1_{it} + \beta_5 NPLs_{it} + \beta_6 SIZE_{it} + \beta_7 PGR_{t} \\
+ \beta_8 GDPGR_{t} + \beta_9 INF_{t} + \beta_{10} IR_{t} + \beta_{11} ER_{t} + \varepsilon_{it}
\end{aligned}
\tag{4.2}
$$

and

$$
\begin{aligned}
\ln(Z_{it}) = const + \alpha \ln(Z_{it-1}) + \beta_1 CE_{it} + \beta_2 SHADOW_{it} + \beta_3 SFTF_{it} \\
+ \beta_4 T1_{it} + \beta_5 NPLs_{it} + \beta_6 SIZE_{it} + \beta_7 PGR_{t} \\
+ \beta_8 GDPGR_{t} + \beta_9 INF_{t} + \beta_{10} IR_{t} + \beta_{11} ER_{t} + \varepsilon_{it}
\end{aligned}
\tag{4.3}
$$

where $SROE_{it}$ is the shadow return on equity of bank i at time t, calculated from equation (4.19), in which higher values suggest higher levels of profitability for banks. Based on the proposition that "*the negative of the derivative of the variable cost function with respect to this fixed input is the input's shadow price*" (Fethi, Shaban and Weyman-Jones, 2012, page 77), the shadow return on equity can be expressed as the negative of the derivative of the bank's cost function with respect to equity. A stochastic frontier cost specification is proposed in equation (4.13) in section 4.4.1b. Then $SROE_{it}$ is estimated through equation (4.19) as the negative of the elasticity of the bank's total cost relative to the level of equity (see page 234). As analysed in section 4.3.1, the return on equity ratio is preferred over the net interest margin and return on assets ratio as the profitability measure in our study. Furthermore, instead of an accounting value of the return on equity ratio, $SROE_{it}$ is used as our profitability proxy because it is based on the frontier cost function and thus is more reliable and closer to the true return on equity (see a detailed comparison of accounting return on equity ratio and shadow return on equity ratio on page 204 of section 4.3.1).

$\ln(Z_{it})$ is the natural logarithm form of the Z-score of bank i in year t, calculated as the sum of bank return on assets ratio and capital to assets ratio divided by the standard deviation of return on assets. As discussed in section 4.3.2, the Z-score is applied as the appropriate stability indicator for sample banks in this chapter. However, the natural logarithm of the Z-score is used since raw Z-scores tend to be highly skewed. In addition, we use a four-year rolling window to calculate the standard deviation of return on assets ratio to permit time variation in the denominator. Similar modifications were used by Hou and Wang (2016) and De-Ramon, Francis and Straughan (2018).

$SROE_{it-1}$ is the first-order lagged term of the dependent variable $SROE_{it}$, addressing potential persistence concerns in the estimation of equation (4.2). Similarly, $\ln(Z_{it-1})$ is the first-order lagged component of the dependent variable $\ln(Z_{it})$, accounting for potential time series persistency in the estimation of equation (4.3). The rationale for the inclusion of lagged components is that most economic relationships are dynamic. Since bank performance in previous time periods may affect future business decisions (e.g., Athanasoglou, Brissimis and Delis, 2008; Wooldridge, 2013; and Badunenko and Kumbhakar, 2017), $SROE_{it-1}$ and $\ln(Z_{it-1})$ are incorporated as dynamic components in our baseline equations (4.2) and (4.3)[138].

[138] We estimate equation (4.2) with different $SROE_{it}$ lags and select the first-order lag for the main study based on the test result of Akaike's/Schwarz's Bayesian information criteria (as it yields the smallest

The coefficient on $SROE_{it-1}$ and $\ln(Z_{it-1})$, α, takes a value between 0 and 1, implying the profitability and stability of examined banks persist over the sample period. Both profitability and stability will finally return to their average levels, and a value of α approaching 0 implies a high speed of adjustment, whereas a value close to 1 indicates a low speed of adjustment.

CE_{it} denotes the cost efficiency score of bank i in year t, and takes a value between 0 and 1; a higher value indicates greater cost efficiency. To estimate cost efficiency, a stochastic frontier cost function is specified, as in equation (4.13); see section 4.4.1b for a detailed discussion. As explained in section 4.2, compared with simple measures of bank efficiency (e.g., the cost to income ratio), CE_{it} is a comprehensive and robust efficiency proxy. $SHADOW_{it}$ represents the shadow banking activities to total assets ratio of bank i at time t. As was pointed out in section 2.7, we simply define Chinese banks' shadow banking activities are banks' practices to offer liquidity to the system without increasing loans to avoid violating various loan regulations. In this chapter, only banks' shadow banking activities are considered in the estimations[139]. Following Hou et al. (2018), banks' shadow banking operations are proxied by the sum of repos and cash collateral, loans and advances to banks, guarantees, and acceptances and documentary credits.

$SFTF_{it}$ is the short-term wholesale funding to total funding ratio of bank i in year t; it suggests the bank's funding strategy, and is used to investigate whether the profitability and stability of Chinese banks can benefit from the utilisation of short-term wholesale funds. $T1_{it}$ refers to the Tier 1 regulatory capital ratio of bank i at time t, measured as Tier 1 capital minus regulatory deduction as a percentage of bank risk-weighted assets. This ratio is introduced to disclose the responses of bank profitability and stability to changes in capital strength. The impact of asset quality

test value).

[139] As discussed in section 2.7, China has a bank-centred shadow banking market; that is, shadow banking activities mainly take place inside the banking system, with commercial banks playing a major role and only a small share of shadow banking operations being undertaken by non-bank financial intermediaries (Li and Lin, 2016).

on the profitability and stability of sample banks is inspected through consideration of $NPLs_{it}$. $NPLs_{it}$ is the non-performing loans ratio of bank i at time t, calculated as the ratio of non-performing loans to total outstanding loans. The higher the ratio, the poorer the credit quality. $SIZE_{it}$ denotes the natural logarithm of total assets of bank i in year t. In the estimation, we condition equations (4.2) and (4.3) on bank size. Overall, the six profitability/stability variables discussed above, i.e., CE_{it}, $SHADOW_{it}$, $SFTF_{it}$, $T1_{it}$, $NPLs_{it}$ and $SIZE_{it}$, are the selected bank-specific variables in equations (4.2) and (4.3).

PGR_t refers to the annual growth rate of profits of Chinese state-owned enterprises in year t, and is regarded as an industry-specific profitability and stability variable in regressions (4.2) and (4.3) respectively. In China, the assets of Chinese banks have been tied up with state-owned firms through substantial government-directed loans. Indeed, the Chinese government offers considerable financial support to state-owned firms. For example, government-directed loans are normally granted at lower than market interest rates. Nevertheless, the majority of stated-owned firms have operated in deficit during the past two decades, which has weakened their debt-servicing ability and amplified the credit risk of Chinese banks via an increase in outstanding non-performing loans (He and Wang, 2009 and Chang et al., 2014). In this scenario, the profitability and stability performance of banks might be hampered. Furthermore, Chang et al. (2014) point out that state-owned enterprises might deliberately take on excessive risk (and hence induce even higher rates of default on bank loans) based on their perception that they will receive more government support if they experience financial distress. Accordingly, PGR_t is introduced to take into account of potential contagion effects on the profitability and stability of Chinese banks flowing from the performance of state-owned enterprises.

$GDPGR_t$ and INF_t are the national annual GDP growth rate and national annual inflation rate in year t. The national annual interest rate at time t, is denoted IR_t, is included to account for the effects of monetary policy on bank profitability and stability, and ER_t is the exchange rate (against US dollar) averaged over year t, which captures the adverse impact of shifts in exchange rate (i.e., exchange rate risk).

These four variables which characterise the environment in which Chinese banks operate are the considered macroeconomic variables in equations (4.2) and (4.3). Finally, ε_{it} represents the function error term.

It is worth noting that model specifications (4.2) and (4.3) consider the implications of those Chinese banking reforms discussed in Chapter 2 on bank profitability and stability. More specifically, how those reforms (i.e., the NPLs disposal and bank recapitalisation) significantly improve the asset quality and capitalisation of Chinese banks are detailly analysed in sections 2.5 and 2.6. Correspondingly, the non-performing loans ratio ($NPLs_{it}$) and Tier 1 regulatory capital ratio ($T1_{it}$) are incorporated in specifications (4.2) and (4.3) to capture the influences of the NPLs disposal and recapitalisation on bank performance over the sample period 2005-2015. Besides, as stated in section 2.3, the more mature banking operations following bank restructuring reforms substantially accelerate China's economic growth, resulting in three decades of 10% compound annual real GDP growth. Such implication is addressed by including $GDPGR_t$ in our specifications. Similarly, the inclusion of IR_t reflects our consideration of exploring the effects of interest rate liberalisation (as discussed in section 2.5) on bank earnings and soundness.

Then, as was pointed out in section 4.2, in light of the policy debate over 'too big to fail', the effects of TBTF status on bank profitability and stability are examined. That is, to account for the significance of 'too big to fail', in the baseline equations we incorporate the $TBTF_i$ dummy variable and its interaction term with $T1_{it}$. Thus, regressions (4.2) and (4.3) become:

$$\begin{aligned} SROE_{it} = const + \alpha SROE_{it-1} + \beta_1 CE_{it} + \beta_2 SHADOW_{it} + \beta_3 SFTF_{it} \\ + \beta_4 T1_{it} + \beta_5 NPLs_{it} + \beta_6 SIZE_{it} + \beta_7 TBTF_i + \beta_8 T1_{it} \\ * TBTF_i + \beta_9 PGR_t + \beta_{10} GDPGR_t + \beta_{11} INF_t + \beta_{12} IR_t \\ + \beta_{13} ER_t + \varepsilon_{it} \end{aligned} \tag{4.4}$$

and

$$\ln(Z_{it}) = const + \alpha\ln(Z_{it-1}) + \beta_1 CE_{it} + \beta_2 SHADOW_{it} + \beta_3 SFTF_{it} + \beta_4 T1_{it} + \beta_5 NPLs_{it} + \beta_6 SIZE_{it} + \beta_7 TBTF_i + \beta_8 T1_{it} * TBTF_i + \beta_9 PGR_t + \beta_{10} GDPGR_t + \beta_{11} INF_t + \beta_{12} IR_t + \beta_{13} ER_t + \varepsilon_{it} \tag{4.5}$$

where $TBTF_i$ is a dummy variable that takes the value of 1 for the 15 Chinese TBTF banks (as identified in section 3.3.2)[140], or 0 otherwise.

Moreover, to perform a thorough investigation of environmental effects, another set of industry-specific variables ($CAPGDP_t$, $SHIBOR_t$ and $ALIBOR_t$) and one macroeconomic variable ($AGDPGR_t$) are added to the baseline models (4.2) and (4.3). Accordingly, the extended model specifications take the following forms:

$$SROE_{it} = const + \alpha SROE_{it-1} + \beta_1 CE_{it} + \beta_2 SHADOW_{it} + \beta_3 SFTF_{it} + \beta_4 T1_{it} + \beta_5 NPLs_{it} + \beta_6 SIZE_{it} + \beta_7 PGR_t + \beta_8 GDPGR_t + \beta_9 INF_t + \beta_{10} IR_t + \beta_{11} ER_t + \beta_{12} CAPGDP_t + \beta_{13} SHIBOR_t + \beta_{14} ALIBOR_t + \beta_{15} AGDPGR_t + \varepsilon_{it} \tag{4.6}$$

and

$$\ln(Z_{it}) = const + \alpha\ln(Z_{it-1}) + \beta_1 CE_{it} + \beta_2 SHADOW_{it} + \beta_3 SFTF_{it} + \beta_4 T1_{it} + \beta_5 NPLs_{it} + \beta_6 SIZE_{it} + \beta_7 PGR_t + \beta_8 GDPGR_t + \beta_9 INF_t + \beta_{10} IR_t + \beta_{11} ER_t + \beta_{12} CAPGDP_t + \beta_{13} SHIBOR_t + \beta_{14} ALIBOR_t + \beta_{15} AGDPGR_t + \varepsilon_{it} \tag{4.7}$$

where $CAPGDP_t$ denotes the market capitalisation to GDP ratio at time t, reflecting the development of the Chinese equity market. A higher ratio implies a more efficient equity market. We adopt this factor to control for the increasing association between

[140] To recap, these 15 Chinese TBTF banks are the Agricultural Bank of China, Bank of China, Bank of Communications, China CITIC Bank, China Construction Bank, China Everbright Bank, China Merchants Bank, China Minsheng Banking Corporation, China Zheshang Bank, Hua Xia Bank, Industrial Bank, Industrial and Commercial Bank of China, Ping An Bank, Postal Savings Bank of China, and Shanghai Pudong Development Bank. See detailed discussions of the systemic importance of these banks in the Chinese banking market in section 3.3.2.

the Chinese banking market and the equity market under the ongoing bank recapitalisation process in China. Interestingly, dynamic linkages between the Chinese equity market and the banking market have not been focused upon in previous literature on Chinese bank profitability during the past few decades (Tan, Floros and Anchor, 2017)[141]. Earlier studies have mainly examined the significance of bank-based financial developments and economic growth. To fill this gap with more recent evidence, $CAPGDP_t$ is investigated in our study. $SHIBOR_t$ is the Shanghai 3-month interbank offered rate in year t, depicting the funding cost of interbank borrowings.

$ALIBOR_t$ and $AGDPGR_t$ respectively represent the aggregated 3-month interbank offered rate and aggregated annual GDP growth rate of the US, UK, Europe, Japan and Hong Kong in year t[142] – $ALIBOR_t$ indicating the funding costs and $AGDPGR_t$ the levels of economic growth. They are proposed to inspect the potential effects of overseas economic conditions on Chinese banks' profitability and stability. That is, we assume financial uncertainties that emerge from the US, UK, European, Japanese and Hong Kong economies can affect the performance of Chinese banks through contagion effects[143]. These five particular economies are considered because the China Financial Stability Report (2016) suggested that these five regions have close connections with the Chinese banking industry via capital flows and interbank exposures. See Table 4.1 for an overview of all the variables included in our bank profitability and stability regressions (equations 4.2-4.7).

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[141] One of the few Chinese studies on the association between the equity market and banking market is that of Tan, Floros and Anchor (2017). They investigate the effects of stock market development on bank profitability within the context of Chinese commercial banks over 2003-2013.

[142] The aggregated interbank offered rate and aggregated annual GDP growth rate entered in regressions (4.6) and (4.7) are the indicators we construct from extracting the variance of each respective interbank offered rate and annual GDP growth rate of the proposed five economies via factor analysis Taking the interbank offered rate as an illustration, a_t, b_t, c_t, d_t, and e_t are the actual interbank offered rates for the US, UK, Europe, Japan and Hong Kong respectively in year t. The factor analysis is then employed to reduce these five variables into one new factor. It extracts maximum common variances from a_t, b_t, c_t, d_t, and e_t and puts them into a newly generated common score, named $ALIBOR_t$ in our case.

[143] To illustrate, a US recession may induce reactionary market downturns in China as these two markets are closely correlated with each other. The resultant financial uncertainties in the domestic market could lead to a reduction in profitability of Chinese banks through increased funding costs as lenders will require higher return rates to compensate for the higher risks that they take during such periods of economic distress.

To estimate equations (4.2)-(4.7), the system generalised method of moments (GMM) estimator, proposed by Arellano and Bover (1995) and Blundell and Bond (1998), is employed in this chapter as specified in equation (3.27). The rationale for us to choose the system GMM method to estimate dynamic panel data regression was set out in section 3.4.2. To recap, the system GMM estimator not only accounts for possible panel heteroscedasticity and autocorrelation problems, but also addresses endogeneity issues raised by the presence of lagged terms and allows the inclusion of exogenous explanatory factors and instrumental variables. Specifically, the inclusion of lagged terms, $SROE_{it-1}$ and $\ln(Z_{it-1})$, gives rise to the limitation that unobserved panel-level effects are correlated with lagged variables, which violates the assumption of strict exogeneity and hence leads to inconsistent estimators (Simper, Dadoukis and Bryce, 2019). The system GMM method overcomes this concern by first differencing the regression to erase the individual effects, and estimation then becomes a straightforward instrumental variables issue, and therefore allows for the inclusion of potentially endogenous regressors (see equations 3.25 and 3.26). Furthermore, as shown in equation (3.27), the system GMM estimator builds a system of equations, which consists of the equation in differences and in levels in a stacked form, suggesting both lagged differences and levels can be utilised as instrumental variables when lagged levels are perceived to be weak instruments for the differenced equation[144]. See a detailed introduction of the system GMM estimator on pages 112-116 of Chapter 3.

In system GMM estimation, with respect to model specifications (4.2)-(4.7), industry-specific and macroeconomic variables – PGR_t, $GDPGR_t$, INF_t, IR_t, ER_t, $CAPGDP_t$, $SHIBOR_t$, $ALIBOR_t$ and $AGDPGR_t$ – are deemed to be strictly exogenous, while lagged variables, $SROE_{it-1}$ and $\ln(Z_{it-1})$, are treated as predetermined regressors, where the standard treatment (Roodman, 2009) is followed, instrumentalising them with their own first lag. The bank-specific variables are potentially endogenous, given the possibility of reverse causality between dependent variables and bank-specific regressors (Athanasoglou, Brissimis and Delis, 2008). Taking equation (4.2) as an

[144] The lagged levels are weakly correlated with subsequent first differences when the variance of u_i is larger than the variance of v_{it} and/or when the series are highly persistent.

example, banks with better management efficiency are likely to have lower costs and thereby generate higher levels of return. Such a correlation might also flow in the opposite direction, however: more profitable banks have the ability to hire more personnel and hence lower their operational efficiency. This illustrates the presence of reverse causality between bank profitability and its regressors.

Accordingly, the use of instrumental variables (IVs) is called for to solve the potential endogeneity issues discussed above, as IVs are deemed to be solely correlated with possibly endogenous regressors and not related to the function error term (Roodman, 2009a). The IV regression is integral to the system GMM estimation, although several post-estimation diagnostics need to be conducted. The identification of valid IVs and the related post-estimation tests are specifically analysed on pages 114-116 in Chapter 3. To recall, the instrument proliferation issue is addressed by comparing the number of IVs utilised in estimation with the number of groups observed in the sample dataset. The validity of the subsets of GMM-style instruments and joint validity of all used IVs are examined by difference in Hansen test and Hansen J-statistic, respectively. A standard Arellano-Bond test for AR (1) and AR (2) checks potential serial correlation problems, and Windmeijer's (2005) finite sample correction is employed to deal with potential downward bias in estimators. If estimations satisfy the above post-estimation diagnostics, our specifications will be free from the main bias and, hence, the estimators produced will offer a basis for the identification of the determinants of bank profitability and stability in China.

Table 4.1: Variables incorporated in the proposed profitability and stability specifications (4.2)-(4.7).

Incorporated variables	Notation	Measurement	Testing effects
Dependent variables:			
Shadow return on equity	$SROE$	Estimated by equation (4.19)	Profitability proxy
Z-score	lnZ	$\ln(\frac{Return\ on\ assets + capital\ to\ assets}{\sigma(Return\ on\ assets)})$	Stability proxy
Bank specific variables:			
Cost efficiency scores	CE	Estimated by equations (4.13) and (4.14)	Management efficiency
Shadow banking activities ratio	$SHADOW$	$\frac{Repos\ and\ cash\ collateral + loans\ and\ advances\ to\ banks + guarantees + acceptances\ and\ documentary\ credits}{Total\ assets}$	Shadow credits
Short-term wholesale funding to total funding ratio	$SFTF$	$(Interbank\ borrowings + certificates\ of\ deposit + short\ term\ bonds)/total\ funding$	Funding strategy
Tier 1 regulatory capital ratio	$T1$	$\frac{Tier\ 1\ capital - Regulatory\ deductions}{Risk\ weighted\ assets} * 100\%$	Capital strength
Non-performing loans ratio	$NPLs$	$Non\ performing\ loans/total\ outstanding\ loans$	Asset quality
Size	$SIZE$	$\ln(total\ assets)$	Size
Too big to fail	$TBTF$	A dummy variable that takes the value of 1 for the 15 Chinese TBTF banks, or 0 otherwise.	TBTF status
Industry specific variables:			
Growth rate of profits of state-owned enterprises	PGR	Annual growth rate of profits of state-owned enterprises	Risk contagion effect
Market capitalisation to GDP ratio	$CAPGDP$	$Market\ capitalisation/GDP$	Development of the equity market
3-month Shanghai interbank offered rate	$SHIBOR$	3-month short-term interbank offered rate	Funding costs

Aggregated interbank offered rate	$ALIBOR$	Aggregated interbank offered rate of the US, UK, Europe, Japan and Hong Kong via factor analysis	Risk contagion effect
Macroeconomic variables:			
GDP growth rate	$GDPGR$	National annual GDP growth rate	Procyclicality effect
Inflation rate	INF	National annual inflation rate	Procyclicality effect
Interest rate	IR	National annual interest rate	Monetary policy
Exchange rate	ER	National annual exchange rate (against US dollar)	Exchange rate risk
Aggregated GDP growth rate	$AGDPGR$	Aggregated annual GDP growth rate of the US, UK, Europe, Japan and Hong Kong via factor analysis	Risk contagion effect

The construction of $ALIBOR$ *and* $AGDPGR$ *is explained in footnote 142.*
The 15 Chinese TBTF banks are the Agricultural Bank of China, Bank of China, Bank of Communications, China CITIC Bank, China Construction Bank, China Everbright Bank, China Merchants Bank, China Minsheng Banking Corporation, China Zheshang Bank, Hua Xia Bank, Industrial Bank, Industrial and Commercial Bank of China, Ping An Bank, Postal Savings Bank of China, and Shanghai Pudong Development Bank.

Source: Author's own calculations

4.4.1b Stochastic Cost Function

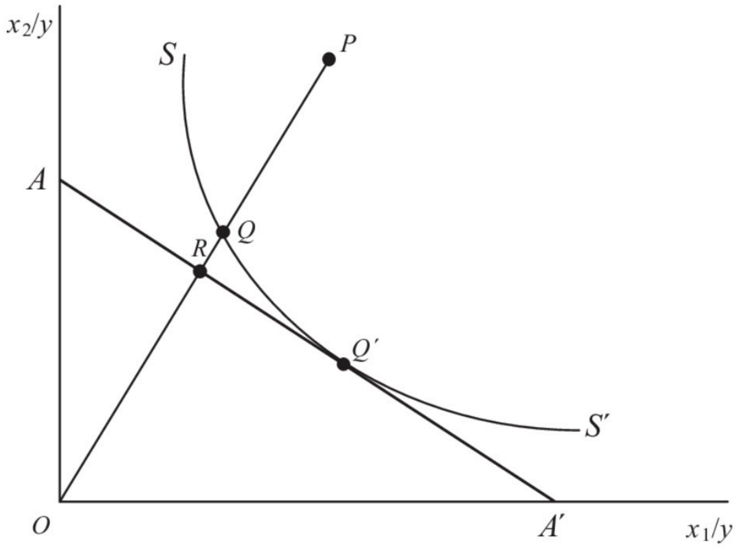
Farrell (1957) extends the theoretical concepts in Debreu (1951) and Koopmans (1951) and is the first empirical paper to measure the economic efficiency of firms. In general, Farrell (1957) divides overall economic efficiency into two parts, the technical efficiency and allocative efficiency. The technical efficiency considers the amount of input needed for the production of a given level of output, regardless of the costs of these factors, while allocative efficiency gives firms the advantage of managing a given activity with less costly resources (Brissimis, Delis and Tsionas, 2010)[145]. Technical and allocative efficiency jointly define the cost efficiency of a firm by considering both technical abilities and production costs.

Farrell (1957) assumes that only two inputs are employed by a firm to produce a single output, at point P in Figure 4.1. That is, the firm's input price ratio is indicated by slope AA' in Figure 4.1, which represents various combinations of inputs that demand the same level of expenditure, while the curve SS' exhibits all possible input combinations the firm can generate if it is perfectly efficient. Hence, cost minimisation will be achieved at point Q', where AA' and SS' intersect. At this intersection, the production of the firm is considered to be efficient, suggesting that the input combination at Q' is both technically and allocatively efficient. Nevertheless, since point P shows the exact combination of inputs for the firm, technical inefficiency arises as the firm will produce the same level of output with fewer inputs by moving the combination from P to Q. Moreover, producing at P means the firm has made an improper selection of the combination of inputs at the given prices, thus incurring more costs than if it had produced at point Q'[146] (allocative inefficiency).

[145] Allocative efficiency reflects the ability of a firm to use the inputs in optimal proportions, given their respective prices.

[146] The firm's technical efficiency is expressed as the ratio OQ/OP (or 1-QP/OP). Allocative efficiency is constructed as OR/OQ.

Figure 4.1: The concept of cost efficiency.



Source: Farrell (1957)

Banking studies have used a wide range of methods and applications to measure cost efficiency – see Fethi and Pasiouras (2010) and Quaranta, Raffoni and Visani (2018) for an overview in the literature. The two main estimation methods have been the non-parametric method of Data Envelopment Analysis and the parametric method of Stochastic Frontier Analysis (Goddard, Molyneux and Williams, 2014). Data Envelopment Analysis (DEA), proposed by Charnes, Cooper and Rhodes (1978), is designed to analyse observations obtained from Decision Making Units (DMUs) for producing units, which are respectively defined by designated inputs and multiple outputs. Accordingly, it entails a wide range of models offering an efficiency measure characterised as the maximum value of the ratio of the weighted sum of outputs to the weighted sum of inputs. This estimation approach is intended to identify an efficient DMUs frontier that 'envelopes' the other units by mathematical (normally linear) programming.

Due to its advantage of easy handling of multiple inputs-outputs, DEA has been adopted in numerous empirical studies on bank efficiency. Paradi, Rouatt and Zhu (2011) found that there were about 280 banking research papers that employed DEA to estimate efficiency published between 1985 and 2011. These studies do not presume any specific functional form for the bank frontier function and examine the degree to which total efficiency in the banking market can enhance and rank the efficiency scores of DMUs. Nonetheless, DEA exposes the natural limitations to a non-parametric approach. For instance, DEA estimation is particularly sensitive to outliers, and the modelling can result in a large percentage of efficient DMUs if the number of proposed inputs-outputs is larger than the number of sample observations (Olesen and Petersen, 2016). More significantly, DEA assumes the model inputs and outputs are homogeneous, and yields biased measures when they are in practice heterogeneous. It also posits that inputs and outputs are measured without putting forward any axioms on the distributional structure of deviations from the best structure frontier and without statistical noise (Quaranta, Raffoni and Visani, 2018).

A parametric method, Stochastic Frontier Analysis (SFA), proposed by Meeusen and van Den Broeck (1977) and Aigner, Lovell and Schmidt (1977), overcomes such limitations because it permits the appearance of noise and the identification of the efficiency frontier[147]. The noise from the inefficiency term calls for parametric restrictions on the shape of the frontier. Accordingly, SFA treats the efficient frontier as a parametric function, and takes account of possible random shocks. In particular, this modelling technique assumes the distribution of systematic deviations can be assigned to two components, i.e., the inefficiency term and random error. The efficiency estimates are derived by disengaging these two components while decomposing the residual of the proposed parametric function of banks' production process into two parts: the skewed part, which is the inefficiency, and the symmetric part of the error (Battese and Coelli, 1995). In this chapter, SFA is preferred over DEA because it hypothesises the frontier shape, constructs confidence intervals allowing for random errors and distinguishes between error terms and the inefficiency term.

[147] Farrell (1957) extends the theoretical concepts in Debreu (1951) and Koopmans (1951) and is the first paper to empirically examine productive efficiency in the context of a US agriculture dataset. His work defines cost efficiency and its corresponding components in an econometric sense. It has given rise to the trend of combining technical inefficiency with specific one-sided error distributions in the empirical banking literature. Built on Farrell (1957) and accompanied with advancements in Aigner and Chu (1968), Timmer (1971), Seitzv (1971) and Richmond (1974), SFA is developed and first practised in Meeusen and Van Den Broeck (1977) and Aigner, Lovell and Schmidt (1977).

Consequently, to estimate cost efficiency and shadow return on equity ratio for the sample of banks, following Battese and Coelli (1995), the following generalised stochastic frontier cost function for panel data can be used:

$$TC_{it} = C(y_{it}, w_{it}, z_{it};\ \beta) + u_{it} + v_{it}$$
$$u_{it} = \delta E_{it} + \lambda_{it} \tag{4.8}$$

where TC_{it} refers to the total costs for the ith bank in year t, and $C(y_{it}, w_{it}, z_{it};\ \beta)$ is the estimated cost frontier in which w_{it} and y_{it} are sets of input prices and output quantities for bank i in year t. Other control variables are represented by z_{it}, and β denotes a group of technology parameters to be estimated, and bank inefficiency term is denoted u_{it}. E_{it} is a vector of measured variables that are considered to define bank inefficiency, δ and λ_{it} are the estimated parameters and random error term respectively, and the model statistical noise is denoted v_{it}.

Based on the generalised cost function (4.8), our specific econometric regression takes the following form:

$$\begin{aligned} lnTC_{it} = const &+ \sum_{n=1}^{3} \alpha_n \ln y_{nit} + \sum_{k=1}^{3} \beta_k \ln w_{kit} \\ &+ {}^{1}\!/_{2} \Bigg[\sum_{n=1}^{3} \sum_{j=1}^{3} \sigma_{nj} \ln y_{nit} \ln y_{jit} \\ &+ \sum_{k=1}^{3} \sum_{l=1}^{3} \gamma_{kl} \ln w_{kit} \ln w_{lit} + \sum_{n=1}^{3} \sum_{k=1}^{3} \delta_{nk} \ln y_{nit} \ln w_{kit} \Bigg] \\ &+ u_{it} + v_{it} \end{aligned} \tag{4.9}$$

where $lnTC_{it}$ is the logarithm form of observed total costs for bank i in year t, $\ln y_{nit}$ and $\ln w_{kit}$ denote the logarithm of the nth output and the logarithm of the kth input price for the ith bank at time t. To select appropriate inputs and outputs for estimation, as explained in section 3.4.3a, among the three theories of the production, intermediation and value-added approach, the intermediation approach is followed[148]. To recall, this preference is determined by prior studies, data constraints and the legislation governing the Chinese banking system. This approach is favoured in our study since it is especially relevant in the examination of bank efficiency during the transition from a strictly regulated banking sector to a much more liberalised sector, as in the Chinese case. That is, since the opening up of the banking market and the liberalisation of the banking sector, which had long been used as a mechanism for the central government to transfer huge sums to meet public policy goals, Chinese banks have focused on performing the intermediation role to generate profits (Denizer, Dinc and Tarimcilar, 2007). Consequently, the intermediation approach is more relevant as it views banks as asset transformers whose task is to transform money borrowed from depositors into money lent to borrowers. Following the intermediation assumption, personnel expenses, total interest expenses and other operating expenses are defined as inputs, while gross loans, other earning assets and loans and advances to banks are defined as outputs for above cost specification (4.9). Bank total costs are proxied by the sum of personnel expenses, total interest expenses and other operating expenses.

The following standard symmetry restrictions are imposed on the cost specification (4.9):

$$\sigma_{nj} = \sigma_{jn} \; and \; \gamma_{kl} = \gamma_{lk} \tag{4.10}$$

In addition, to ensure the linear homogeneity of input prices, the following restrictions are imposed:

$$\sum_k \beta_k = 1, \qquad \sum_{kl} \gamma_{kl} = 0, \qquad \sum_{nk} \delta_{nk} = 0 \tag{4.11}$$

Then, taking risk control variables into consideration, the cost function (4.9) becomes:

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148 A comparison of three dominant modelling theories (the production, intermediation and value-added approaches) in the literature that determine the input-output mix used in efficiency estimation is presented in section 3.4.3a, which discusses the rationale for us to follow the intermediation approach to select bank inputs and outputs for estimation.

$$
\begin{aligned}
lnTC_{it} = const &+ \sum_{n=1}^{3} \alpha_n \ln y_{nit} + \sum_{k=1}^{3} \beta_k \ln w_{kit} \\
&+ {}^{1}\!/_{2} \left[\sum_{n=1}^{3} \sum_{j=1}^{3} \sigma_{nj} \ln y_{nit} \ln y_{jit} \right. \\
&\left. + \sum_{k=1}^{3} \sum_{l=1}^{3} \gamma_{kl} \ln w_{kit} \ln w_{lit} + \sum_{n=1}^{3} \sum_{k=1}^{3} \delta_{nk} \ln y_{nit} \ln w_{kit} \right] \qquad (4.12) \\
&+ \varphi_1 lnz_{it} + {}^{1}\!/_{2}\, \varphi_2 lnz_{it}^2 + \sum_{n=1}^{3} \rho_n \ln y_{nit}\, lnz_{it} \\
&+ \sum_{k=1}^{3} \zeta_k \ln w_{kit} lnz_{it} + u_{it} + v_{it}
\end{aligned}
$$

where lnz_{it} is the natural logarithm of risk control variables considered for the ith bank in year t. The inclusion of risk variables in efficiency estimation is explained in section 3.4.3b. To recap, if managers' risk preferences are neglected when modelling bank costs, the way costs vary with outputs can change substantially because of systematic differences in risk-taking among institutions (Hughes and Mester, 2013). Hence, omitting risk considerations can lead to biased estimates of cost efficiency[149]. In equation (4.12), equity, non-performing loans and loan loss provision are added as risk control variables as they give the best picture of the risk behaviours in the Chinese banking system across the observation period. That is, equity reflects the regulations imposed by Basel III; loan loss provision indicates the risk-taking of sample banks engaging in shadow banking activities; and Chinese banks have historically been burdened by a large number of non-performing loans.

Moreover, to account for changes in technology over the long sample period, time trend variables are generated and included in (4.12), and the equation becomes:

[149] Moreover, the need to incorporate risk factors into the cost function has been addressed in several recent empirical studies estimating the cost efficiency of the Chinese banking industry, such as Dong et al. (2016) and Tan, Floros and Anchor (2017).

$$
\begin{aligned}
lnTC_{it} = const &+ \sum_{n=1}^{3} \alpha_n \ln y_{nit} + \sum_{k=1}^{3} \beta_k \ln w_{kit} \\
&+ {}^{1}/_{2} \left[\sum_{n=1}^{3} \sum_{j=1}^{3} \sigma_{nj} \ln y_{nit} \ln y_{jit} \right. \\
&\left. + \sum_{k=1}^{3} \sum_{l=1}^{3} \gamma_{kl} \ln w_{kit} \ln w_{lit} + \sum_{n=1}^{3} \sum_{k=1}^{3} \delta_{nk} \ln y_{nit} \ln w_{kit} \right] \qquad (4.13) \\
&+ \varphi_1 lnz_{it} + {}^{1}/_{2}\, \varphi_2 lnz_{it}^2 + \sum_{n=1}^{3} \rho_n \ln y_{nit}\, lnz_{it} \\
&+ \sum_{k=1}^{3} \zeta_k \ln w_{kit} lnz_{it} + \eta_1 T + {}^{1}/_{2}\, \eta_2 T^2 + u_{it} + v_{it}
\end{aligned}
$$

where T is the time trend.

Overall, equation (4.13) estimates cost efficiency using a cost frontier which presumes the minimisation of bank costs is contingent on five things, i.e., managerial inefficiency, risk considerations, time trend, environmental effects and statistical noise. Managerial inefficiency is endogenous and can be studied by estimating efficiency measures of banks in employing inputs to produce outputs, subject to the assumption of cost minimisation. Risk considerations and the time trend are investigated through incorporation of risk control variables and time trend variables in the cost specification. Environmental effects examine the reason for discrepancies in cost efficiency estimates across sample banks. This is accomplished by adding either bank-specific factors or factors exogenous to the cost function. In the context of investigating the banking industry, such factors normally refer to a vector of industry-specific indicators (e.g., competition and concentration), supervisory indicators (e.g., Basel III regulations) and macroeconomic indicators (e.g., GDP and inflation). These factors are beyond the control of the bank, meaning that they are exogenous to a bank's production process, and so are not included in either the inputs or the outputs (Kumbhakar and Lovell, 2003)[150]. The impacts of those factors on bank efficiency can, though, be assessed by

[150] Several banking efficiency studies, including Bos et al. (2009) and Sufian, Kamarudin and Nassir (2016),

efficiency estimation through the means of frontier measures.

Bolt and Humphrey (2010) point out that the empirical literature uses two main approaches for the inclusion of exogenous factors in efficiency estimation. The first includes such variables directly in the deterministic part of the frontier as the aforementioned variables are assumed to directly affect the bank production process (e.g., Battese and Coelli, 1995; Kumbhakar and Lovell, 2003 and Chan and Karim, 2010). The second approach follows a different path and assumes that exogenous factors are directly correlated with the inefficiency. This approach follows a two-step procedure whereby efficiency is estimated in step one without taking exogenous variables into account, and in step two the efficiency scores from step one are regressed on a set of explanatory variables (see, Bonin et al., 2005 and Teclesa and Tabak, 2010). However, the first step in this approach, estimating efficiency without exogenous variables, presents the omitted-variable bias. That is, given that a bank's ability to produce outputs depends both on the utilisation of inputs and the effects of exogenous variables, the regression of outputs on inputs will give biased estimates if inputs and exogenous factors are correlated. This biased inefficiency estimate in the first step in turn results in bias in the second step, when u_{it} is regressed against a group of exogenous variables (Wang and Schmidt, 2002).

Our research follows Battese and Coelli (1995) in using a single-step estimation that directly incorporates exogenous factors in the cost function to address the bias outlined above. Accordingly, the bank-specific inefficiency term (u_{it}) in equation (4.13) can be expressed as a function of a vector of macroeconomic factors characterising the environment in which the production of Chinese banks occurs. That is,

$$u_{it} = \delta_0 + \delta_1 PGR_t + \delta_2 GDPGR_t + \delta_3 INF_t + \delta_4 IR_t + \delta_5 ER_t + \lambda_{it} \qquad (4.14)$$

where PGR_t is the annual growth rate of profits of Chinese state-owned firms in year

provide empirical evidence that suggest omitting exogenous variables during estimation can result in the mis-specification of the efficiency frontier (e.g., the frontier is artificially high or low).

t, measuring the effects of the poor performance of state-owned firms on the (in)efficiency of sample banks[151]. $GDPGR_t$ denotes the national annual GDP growth rate at time t, and shows the impacts of economic growth on cost efficiency. INF_t and IR_t are the national annual inflation rate and annual interest rate in year t, illustrating the implications of inflation and monetary policy on bank cost efficiency. The national annual exchange rate (against the US dollar) in year t is proxied by ER_t, a ratio that captures the adverse impact of shifts in exchange rate (i.e., exchange rate risk). δ_0 denotes the constant term and λ_{it} is the error term. Thus, an inclusive specification is presented in equation (4.14) and, to the best of our knowledge, previous banking efficiency studies have mainly employed a similar set of macroeconomic factors (see, for example, Kumbhakar and Lovell, 2003; Pasiouras, Tanna, and Zopounidis, 2009; Goddard, Molyneux and Williams, 2014 and Diallo, 2018).

Overall, our study is one of only a handful of Chinese studies on bank cost efficiency adopting an all-encompassing interpretation of cost efficiency rather than solely focusing on the standard internal structure (inputs and outputs) estimation. It takes internal complex structures (i.e., inputs-outputs mix), risk control variables and external environmental factors (macroeconomic variables) into consideration when construct the efficiency frontier. In summary, Table 4.2 specifies the variables (inputs, outputs, risk control variables and macroeconomic variables) incorporated in our cost specifications (4.13) and (4.14). Considering the nature of the Chinese banking industry and data constraints, we believe this group of variables captures the majority of the business management characteristics of Chinese banks.

The proposed cost functions (4.13) and (4.14) assume that sample banks in the same environmental settings will produce the same outputs. SFA then measures the distance of the observed cost of each individual bank to that of the theoretical 'best

[151] We assume there are risk contagion effects between the performance of state-owned enterprises and the performance of Chinese banks: see discussions of such effects on page 216 in section 4.4.1a. To recap, as was mentioned, the assets of most Chinese banks are tied up with state-owned enterprises via government-directed loans. Nevertheless, these firms show higher default rates on their bank loans given that they normally operate with deficits, and have moral hazard incentives. In this argumentation, firms' defaults on loans could induce additional operating costs for banks as there are associated costs to recover these non-performing loans, which in turn reduces bank cost efficiency.

practice' bank to obtain cost efficiency scores. Specifically, the stochastic frontier is estimated in two sequential steps. First, cost functions (4.13) and (4.14) are calculated simultaneously via maximum likelihood estimation. Second, inefficiency estimates are yielded using the Battese and Coelli (1988) technique, and specific cost efficiency scores are calculated using the mean of the distribution of $E[exp\ (-u_i|e_i)$, $\varepsilon_{it} = u_{it} + v_{it}$. The obtained scores take a value between 0 and 1. A final efficiency estimate equal to 1 indicates a perfectly cost-efficient bank.

Next, we perform several pre- and post-estimation tests to confirm the validity of the cost specifications presented above. Accordingly, the skewness test on the OLS residuals of equation (4.13) is carried out to examine the validity of its stochastic specification. The underlying assumption is that the distribution of the OLS residuals is positively skewed (i.e., skewing to the right-hand side) for the estimation of a cost function, under the model setting of a composed error term $u_{it} + v_{it}$ (Schmidt and Lin, 1984).

Alternatively, Coelli (1995) proposes a variant test under the null hypothesis that no skewness can be observed. The test statistic is:

$$\text{M3T} = m_3 / \sqrt{6m_2^3/N} \tag{4.15}$$

It suggests that under the null hypothesis, the third moment of the OLS residuals is asymptotically distributed as a normal random variable with mean 0 and variance $6m_2^3/N$. A value of the test statistic falling out of the rejection zone [-1.96, 1.96] proves the presence of a one-sided error term for our stochastic frontier model specification.

In addition to these pre-estimation tests, the post-estimation likelihood ratio test is implemented to check for the absence of the inefficiency term, u_{it}. That is, when the hypothesis that the error term is one-sided is rejected, standard OLS regression is sufficient for the function specification. The SFA estimation, with the composed error term $u_{it} + v_{it}$, takes the dual variance approach, i.e., σ_u^2 and σ_v^2. Thus, the model's total variance is the sum of these two variance terms, and the corresponding likelihood function takes the following form:

$$\lambda = \sigma_u^2/\sigma_v^2 + \sigma_u^2 \tag{4.16}$$

As equation (4.16) shows, the inefficiency term, u_{it}, is a function of a group of exogenous variables. In this sense, the following null hypothesis can be examined to address the absence of inefficiency effects:

$$H_0: \lambda = \delta_0 = \cdots = \delta_5 = 0 \tag{4.17}$$

And the statistic of the likelihood ratio test is computed as:

$$-2[L(H_0) - L(H_1)] \tag{4.18}$$

where $L(H_0)$ denotes to the log likelihood value of our OLS (restricted) model and $L(H_1)$ is the log likelihood value of our SFA (unrestricted) model. The test statistic has a mixed chi-squared distribution with the degree of freedom set to the number of restrictions. We follow the standard developed by Kodde and Palm (1986) (their table 1 offers critical values at various levels of degree of freedom). If the test statistic falls out of the rejection zone, the rejection of the null hypothesis of no cost inefficiency indicates that our SFA model is correctly identified.

Once the robustness of the proposed cost function is confirmed, then, following Hughes, Mester, and Moon (2001) and Fethi, Shaban and Weyman-Jones (2012), sample banks' shadow return on assets ratio can be defined as

$$SROE_{it} = -\partial TC_{it}/\partial EQ_{it} \tag{4.19}$$

where EQ_{it} is the fixed input (equity) variable considered in the cost specification

(4.13). $SROE_{it}$ is measured as the negative of the derivative of the cost function (4.13) relative to the level of equity. On the one hand, as a proxy to analyse the cost of recapitalisation, $SROE_{it}$ calculates the price that banks are willing to pay for their equity capital. In general, higher values of $SROE_{it}$ imply that sample banks are over-leveraged on debt financing and their equity capital is underused, whereas lower values are observed for banks that are leveraged to a lesser degree. On the other hand, as mentioned in section 4.3.1, $SROE_{it}$ is used instead of an accounting value of the return on equity ratio as the profitability indicator in our profitability functions (4.2), (4.4), and (4.6). As a profitability proxy, a higher ratio means a higher level of profitability is experienced by banks.

Finally, linking to Chapter 3, scale inefficiency is estimated under the cost function (4.13) to compare the distribution of two sets of scale inefficiency scores derived respectively from the seemingly unrelated regression in Chapter 3 and the stochastic cost function in this chapter. This comparison can be achieved through the Spearman's rank-order correlation test (see section 4.5.1). Although specific scale inefficiency scores estimated by these two different modelling approaches can be different for each respective bank, the rankings of banks in terms of inefficiency scores should be similar. If the techniques do not rank banks in a similar manner, the policy conclusions proposed in Chapter 3 will be fragile and model dependent. To estimate scale inefficiency, following Evanoff and Israilevich (1995), the cost function (4.13) can be generalised as follows:

$$lnTC_{it} = \Bigg[const + \sum_{k=1}^{3} \beta_k \ln w_{kit} + {}^1\!/_2 \sum_k \sum_l \gamma_{kl} \ln w_{kit} \ln w_{lit} + \varphi_1 lnz_{it} + {}^1\!/_2\, \varphi_2 lnz_{it}^2 + \sum_{k=1}^{3} \zeta_k \ln w_{kit} lnz_{it} + \eta_1 T + {}^1\!/_2\, \eta_2 T^2\Bigg] + \Bigg[\alpha_i + {}^1\!/_2 \sum_i \sum_k \delta_{ik} \ln w_{kit} + \sum_i \rho_i lnz_{it}\Bigg] \ln Q_{it} + {}^1\!/_2\, [\sigma_{nj}]\, (\ln Q_{it})^2 + u_{it} + v_{it} \quad (4.20)$$

where Q_{it} refers to the quantity of bank outputs. To simplify the above equation, coefficients a, b, c are used to represent the term in each set of brackets in equation (4.20):

$$\ln TC = \mathrm{a} + \mathrm{b} \ln Q + {}^1\!/_2\, c\, (\ln Q)^2 \quad (4.21)$$

Equation (4.21) reveals the underlying cost structure of sample banks. Equations (3.11)-(3.17) on pages 104-106 present in detail the process of generating scale inefficiency estimates based on the above simplified cost function. To recall, in the end, scale inefficiency scores (SI) can be expressed as:

$$\mathrm{SI} = e^{(0.5/c)(1-\varphi_{SI})^2} - 1 \quad (4.22)$$

where φ_{SI} is the scale elasticity measure for scale-inefficient banks.

Table 4.2: Variables included in cost specifications (4.13) and (4.14).

Variables	Measurements
Inputs (X):	
X1	Personnel expenses
X2	Total interest expenses
X3	Other operating expenses
Outputs (Y):	
Y1	Gross loans
Y2	Other earning assets
Y3	Loans and advances to banks
Input prices:	
P1	X1 / fixed assets
P2	X2 / average customer deposits
P3	X3 / fixed assets
Risk variables:	
Z1	Equity
Z2	Loan impairment charge (loan loss provision)
Z3	Total impaired loans (non-performing loans)
Macro variables:	
Macroeconomic variables	Annual growth rate of profits of state-owned firms National annual GDP growth rate National annual inflation rate National annual interest rate National annual exchange rate (against US dollar)
Cost variable:	
Total Costs	X1 + X2 + X3

where Y1, Y2 and Y3 are deflated by GDP rebased on 2005, while the ratios as inputs, i.e., X1, X2 and X3, can be ignored. The aim of this step is to remove inflation effects, which are able to distort the efficiency estimation by magnifying or contracting all X and Y from the real values.

Source: Author's own calculations

4.4.2 Data and Summary Statistics

The same dataset constructed and used in Chapter 3 is also employed in this chapter.

To recap, an unbalanced panel sample of 108 Chinese commercial banks is constructed, covering the period 2005-2015. The annual accounting data, eligible and regulatory capital information of sample banks were collected from the Orbis Bank Focus Database and SNL financial Platform. All but one of the industry-specific variables and macroeconomic variables considered in our estimations were obtained from the World Bank Database and European Banking Authority statistical report. One industry-specific indicator, the annual growth rate of profits of Chinese state-owned enterprises, is calculated based on the annual profits figures collected from the National Bureau of Statistics (China).

Moving on to discuss summary statistics, Table 4.3 offers descriptive statistics of variables employed in our profitability and stability specifications (4.2)-(4.7). With respect to $SROE_{it}$, severe externalities of the GFC undermined the earning capacity of Chinese banks, reflected by the sudden drop in the values of $SROE_{it}$ during the crisis. Then, a short while after they had recovered, their profitability entered a further period of distress, up until the end of 2015, given the ratio decreased from 15.18% to 8.96% during 2009 to 2015. Meanwhile, throughout the sample period, the variations of $\ln(Z_{it})$ show that Chinese banks were fairly robust, with only minor deteriorations of bank stability during crisis years (e.g., $\ln(Z_{it})$ declined by 22.25% between 2006 and 2009).

Regarding the bank-specific variables, the cost efficiency performance of sample banks (CE_{it}) shows an overall declining tendency during the period 2005-2015, indicating the increasingly weak cost control capability of banks. In contrast, $SHADOW_{it}$ displays an marked increase over 2005-2011, reaching 40.18% by the end of 2011. The ratio then declined to 25.54% in 2015.

$SFTF_{it}$ began with a high level of about 6.2% in year 2005, followed by a slight rise in the subsequent observation year. However, the Chinese government halted the distribution of several types of money market instruments during the crisis period, resulting in a decline over the next few years (An and Yu, 2018). After the GFC, as discussed, the larger Chinese banks increasingly relied on short-term wholesale funds as their main funding source and so, not surprisingly, the ratio more than doubled between 2011 and 2015, from 1.66% to 4.58% during this period, with a tendency to exceed the pre-crisis level. As indicated in section 2.6, the domestic version of the Basel III capital requirement demands a minimum of 7.5% holding of Tier 1 common equity for Chinese banks. In this case, Table 4.3 shows a sufficient core equity reserve in sample banks over 2006-2015. Overall, $T1_{it}$ increases over the period, peaking 15.1% in 2012. Despite minor reductions witnessed by sample banks in the subsequent three years, an average of 11.86% Tier 1 capital validates banks' strong resilience to expected and/or unexpected future adverse shocks. The $SIZE_{it}$ indicator remains rather steady, with only minor variations over the study period.

Among the industry-specific variables, PGR_t generates the largest variations among all the variables over 2005-2015. Indeed, the majority of state-owned firms normally operated with financial deficits even under the umbrella of heavy government protections. As for $CAPGDP_t$, the listing of large Chinese state-owned commercial banks during 2005 and 2006 significantly enhanced the equity market in China, which gave rise to a temporary abnormal surge in this ratio. To illustrate, $CAPGDP_t$ sharply increased from about 17.58% to a record high level of 126.15% across 2005 to 2007 (see Table 4.3). Then a gradual yet fluctuating upward tendency is seen in China. $SHIBOR_t$ increased to a then record high level of 4.17% in 2008, that is, during the crisis period (which might have been a reflection of liquidity hoarding behaviours in the interbank market in the case of financial distress), then exhibited a cliff-like drop of more than 60% to 1.6% in 2009, which may be attributed to the implementation of the CNY4 trillion capital injection programme by the central government. Nevertheless, this ratio rapidly climbed back and remained at even higher levels after 2011.

Overall, China had a slightly tight macroeconomic environment during the study period. Specifically, $GDPGR_t$ started to slow after the start of the GFC, although it had enjoyed strong growth before 2007. However, the growth ratio was better than those of China's major competitors, given that Japan was suffering negative growth (-0.1%), South Korea was around 3.3% and the rates for the UK and the US were 2.9% and 2.4% respectively during 2011. INF_t showed fluctuations across the period, with the presence of a negative rate in 2009. This sharp decline, from 5.93% to -0.73% over 2008 to 2009, was mainly due to the GFC. From 2012, there were slight reductions in inflation and this downward trend continued through to 2015. Recently, several rounds of interest rate cuts were enforced by the PBOC in order to boost China's slowing economy. IR_t was lowered from 4.73% in 2014 to 4.25% in the following year. ER_t presents a rather stable tendency over the sample period, possibly reflecting the long-term effort of the Chinese government to control the exchange rate. Nevertheless, Table 4.3 shows that the Chinese government permitted a gradual appreciation of the domestic currency from 2005, with the yuan (CNY)[152] appreciating by roughly 24% over 2005-2015, to about 6.23 against the US dollar (US$) by the end of 2015.

In addition, the correlations among these incorporated variables are examined and the results are presented in below Table 4.4. Using the rule of thumb that correlation coefficient values greater than 0.7 indicate worrisome results, it is evident that none of the variables incorporated in equations (4.2)-(4.7) present multicollinearity concerns.

Concerning the summary statistics of variables utilised in the cost specification (4.13), the same set of input-output mix and risk control variables are selected for the stochastic cost function in this chapter as were used in section 3.4.3. The evolutions of bank inputs, outputs and risk variables across the sample period are illustrated in Figures 3.1, 3.2 and 3.3, respectively. See pages 126-129 for a detailed discussion of summary statistics of bank inputs, outputs and risk terms for the whole sample over the examination period of 2005-2015. Moreover, in this section, we further report descriptive statistics for different types of sample banks – see Table 4.5, 4.6, 4.7, 4.8 and 4.9. As shown, on average, Chinese state-owned commercial banks have the highest personnel costs, with a mean value of CNY40840.98 million, followed by joint-stock commercial banks (CNY6618.79 million), rural commercial banks (CNY803.68 million), city commercial banks (CNY632.81 million) and foreign commercial banks (CNY371.11 million). Not surprisingly, for all types of banks, the balance of total

[152] CNY is abbreviation for China yuan, which is the official currency of China.

interest expenses is substantially higher than those for personnel expenses and other operating expenses. This is because the underdeveloped and immature features of Chinese banking system make Chinese banks tend to rely on traditional banking services (i.e., deposit-taking) to produce their earnings.

With respect to input prices, on average, Chinese foreign commercial banks display the highest price levels among all types of banks over the sample duration of 2005-2015. Indeed, the mean of P1 is as high as 5.65 for foreign commercial banks, and the mean of P2 and P3 for this type of banks are 0.04 and 4.67, respectively. Table 4.5 show that state-owned commercial banks exhibit the largest output levels among all groups of banks. More specifically, the mean of gross loans is CNY3750842 million for sample state-owned banks, this figure is roughly 81% higher than that of joint-stock banks (CNY646656.4 million) who are the second largest group of banks in terms of output level. Meanwhile, its balance of other earning assets is CNY1850050 million – this value is almost 7 times as large as joint-stock banks (CNY270806.8 million), around 50 times, 65 times and 262 times bigger than city commercial banks (CNY36546.08 million), rural commercial banks (CNY28272.93 million) and foreign banks (CNY7039.79 million) respectively. Again, compared with the other four types of banks, state-owned banks record the highest balance of loans and advances to banks (CNY785432.9 million). In addition, it can be observed that the lowest mean value of equity (CNY4584.71 million) is reported by the group of Chinese foreign commercial banks. Whereas state-owned commercial banks report the highest equity balance (CNY471125.6 million) – an indication of their outstanding capitalisation performance across the sample period. However, these banks are confronted with the largest risk exposures compared to other types of banks, given their mean of loan loss provision is CNY22765.68 million and their non-performing loans stock is CNY62908.98 million.

Table 4.3: Summary statistics of variables included in the profitability and stability specifications (4.2)-(4.7).

	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
$SROE_{it}$	16.56	16.06	14.04	11.08	15.18	14.90	11.63	10.14	9.94	8.96	8.96
$\ln(Z_{it})$	4.28	4.63	3.75	3.71	3.60	3.78	3.86	4.28	4.30	4.36	4.23
CE_{it}	88.10	89.90	90.90	83.89	84.58	86.13	82.80	81.85	82.25	81.65	81.76
$SHADOW_{it}$	20.57	23.10	28.40	30.63	33.29	39.08	40.18	39.22	34.93	28.15	25.54
$SFTF_{it}$	6.21	6.26	5.38	4.73	4.44	4.01	1.66	2.49	2.93	3.92	4.58
$T1_{it}$	6.94	8.10	9.30	10.63	11.71	11.80	12.72	15.10	11.45	11.70	12.43
$NPLs_{it}$	7.43	2.71	2.30	1.76	1.26	2.03	1.29	1.28	0.90	1.25	1.60
$SIZE_{it}$	13.49	13.43	12.93	12.28	12.11	12.09	12.06	11.81	12.06	12.07	12.15
PGR_t	33.64	33.42	-6.68	4.46	58.70	16.85	-5.00	3.20	-4.50	-21.13	0.68
$CAPGDP_t$	17.58	41.62	126.15	38.72	70.04	66.17	45.18	43.33	41.26	57.53	74.33
$SHIBOR_t$	2.86	2.74	3.33	4.17	1.60	2.45	5.22	4.29	4.44	4.97	3.68
$GDPGR_t$	10.74	12.09	13.64	9.09	8.86	10.10	9.01	7.33	7.23	6.76	6.36
INF_t	1.78	1.65	4.82	5.93	-0.73	3.18	5.55	2.62	2.62	1.92	1.44
IR_t	1.61	2.11	-0.31	-2.33	5.45	-1.06	-1.47	3.52	3.69	4.73	4.25
ER_t	8.19	7.97	7.61	6.95	6.83	6.77	6.46	6.31	6.20	6.14	6.23

Where, $SROE_{it}$: shadow return on equity ratio (%), $ln(Z_{it})$: natural logarithm of bank Z-score, CE_{it}: cost efficiency scores (%), $SHADOW_{it}$: bank shadow exposures to total assets ratio (%), $SFTF_{it}$: short-term funding to total funding ratio (%), $T1_{it}$: Tier 1 regulatory capital ratio (%), $NPLs_{it}$: non-performing loans ratio (%), $SIZE_{it}$: natural logarithm of bank size, PGR_t: annual growth rate of industrial profits (%), $CAPGDP_t$: market capitalisation to GDP ratio (%), $SHIBOR_t$: 3-month Shanghai interbank offered rate (%), $GDPGR_t$: national annual GDP growth rate (%), INF_t: national annual inflation rate (%), IR_t: national annual real interest rate (%), ER_t: national annual exchange rate against US dollar (%).

Source: Author's own calculations

Table 4.4: Correlation matrix of variables included in the proposed profitability and stability specifications.

	$SROE_{it}$	$\ln(Z)$	CE_{it}	$SHADOW_{it}$	$SFTF_{it}$	$T1_{it}$	$NPLs_{it}$	$SIZE_{it}$	PGR_t
$SROE_{it}$	1								
$\ln(Z_{it})$	-0.072	1							
CE_{it}	0.152	-0.051	1						
$SHADOW_{it}$	-0.005	-0.080	-0.185	1					
$SFTF_{it}$	-0.011	0.009	0.145	-0.025	1				
$T1_{it}$	-0.032	0.068	-0.198	0.128	0.103	1			
$NPLs_{it}$	0.089	-0.086	0.103	0.021	-0.026	-0.038	1		
$SIZE_{it}$	-0.025	0.115	0.094	-0.328	-0.126	-0.411	-0.018	1	
PGR_t	0.443	-0.190	0.345	0.026	0.139	-0.019	0.037	0.026	1
$GDPGR_t$	0.495	-0.194	0.203	0.055	0.163	-0.103	0.103	0.102	0.382
INF_t	0.021	-0.078	-0.317	0.133	-0.017	-0.008	0.025	0.012	-0.439
IR_t	-0.262	0.181	0.077	-0.115	-0.065	0.036	-0.072	-0.034	0.041
ER_t	0.496	-0.164	0.346	-0.011	0.198	-0.118	0.118	0.124	0.536
$CAPGDP_t$	0.128	-0.098	0.533	-0.142	0.103	-0.065	0.077	0.064	0.147
$SHIBOR_t$	-0.431	0.171	-0.528	0.055	-0.168	0.051	-0.073	-0.044	-0.682
$ALIBOR_t$	0.301	-0.116	0.233	-0.021	0.162	-0.121	0.096	0.120	0.160
$AGDPGR_t$	-0.324	0.169	0.379	-0.238	-0.010	-0.061	0.025	0.045	-0.476

	$GDPGR_t$	INF_t	IR_t	ER_t	$CAPGDP_t$	$SHIBOR_t$	$ALIBOR_t$	$AGDPGR_t$
$GDPGR_t$	1							
INF_t	0.393	1						
IR_t	-0.653	-0.672	1					
ER_t	0.617	0.180	-0.472	1				
$CAPGDP_t$	0.325	-0.256	0.085	0.330	1			
$SHIBOR_t$	-0.418	0.515	-0.071	-0.560	-0.471	1		
$ALIBOR_t$	0.655	0.430	-0.501	0.547	0.240	-0.180	1	
$AGDPGR_t$	-0.404	-0.267	0.409	-0.258	0.453	0.181	-0.055	1

$SROE_{it}$: shadow return on equity (%), $ln(Z_{it})$: natural logarithm of bank Z-score, CE_{it}: cost efficiency scores (%), $SHADOW_{it}$: bank shadow exposures to total assets ratio (%), $SFTF_{it}$: short-term funding to total funding ratio (%), $T1_{it}$: Tier 1 regulatory capital ratio (%), $NPLs_{it}$: non-performing loans ratio (%), $SIZE_{it}$: natural logarithm of bank size, PGR_t: annual growth rate of industrial profits (%), $GDPGR_t$: national annual GDP growth rate (%), INF_t: national annual inflation rate (%), IR_t: national annual real interest rate (%), ER_t: national annual exchange rate against US dollar (%), $CAPGDP_t$: market capitalisation to GDP ratio (%), $SHIBOR_t$: 3-month Shanghai interbank offered rate (%), $ALIBOR_t$: aggregated interbank offered rate of the US, UK, Europe, Japan and Hong Kong (%), and $AGDPGR_t$: aggregated national annual GDP growth rate of the US, UK, Europe, Japan and Hong Kong (%).

Source: Author's own calculations

Table 4.5: Descriptive statistics of variables selected for equation (4.13) of sample state-owned commercial banks.

Variables	Mean	Std. Dev.	Min	Max
Inputs:				
X1	40840.98	20909.95	5776	77887.48
X2	118970.5	57494.96	18089	248256.5
X3	34123.86	12470.4	10127	58462.12
Input prices:				
P1	0.55	0.16	0.23	0.94
P2	0.02	0.01	0.01	0.04
P3	0.57	0.47	0.28	2.28
Outputs:				
Y1	3750842	1899740	769540	8140871
Y2	1850050	825930.9	385951.3	3488041
Y3	785432.9	408604.8	165634.4	1904833
Risk terms:				
Z1	471125.6	271322.4	80401.95	1228293
Z2	22765.68	14083.38	3850.39	63177.46
Z3	62908.98	36014.54	3098.66	154417
Total costs:				
TC	193935.3	86061.52	33992	370037.3

All values are expressed in millions of CNY.
where X1: Personnel Expenses, X2: Total Interest Expenses, X3: Other Operating Expenses, P1: X1 / Total Assets, P2: X2 / Average Customer Deposits, P3: X3 / Total Assets, Y1: Gross Loans, Y2: Other Earning Assets, Y3: Loans and Advances to Banks, Z1: Equity, Z2: Loan Loss Provision, Z3: Non-performing Loans, TC: X1+X2+X3.

Source: Author's own calculations

Table 4.6: Descriptive statistics of variables selected for equation (4.13) of sample joint-stock commercial banks.

Variables	Mean	Std. Dev.	Min	Max
Inputs:				
X1	6618.79	4839.85	313.11	21416.62
X2	27893.59	22790.87	1706.39	90395.4
X3	5656.95	3735.29	485.48	16609.24
Input prices:				
P1	1.12	0.49	0.24	2.93
P2	0.03	0.01	0.02	0.07
P3	1.03	0.50	0.47	3.25
Outputs:				
Y1	646656.4	436913.8	42544.01	1926695
Y2	270806.8	284179.7	15645.21	1780153
Y3	229023	173979.5	10170.04	820504.6
Risk terms:				
Z1	72735.41	61026.54	3562.05	246787.1
Z2	5333.49	6584.72	160.45	39230.6
Z3	7416.95	5978.42	140.69	32333
Total costs:				
TC	40169.34	30349.65	3045.21	112165.4

All values are expressed in millions of CNY.
where X1: Personnel Expenses, X2: Total Interest Expenses, X3: Other Operating Expenses, P1: X1 / Total Assets, P2: X2 / Average Customer Deposits, P3: X3 / Total Assets, Y1: Gross Loans, Y2: Other Earning Assets, Y3: Loans and Advances to Banks, Z1: Equity, Z2: Loan Loss Provision, Z3: Non-performing Loans, TC: X1+X2+X3.

Source: Author’s own calculations

Table 4.7: Descriptive statistics of variables selected for equation (4.13) of sample city commercial banks.

Variables	Mean	Std. Dev.	Min	Max
Inputs:				
X1	632.81	832.51	14.24	6256.42
X2	3198.13	5054.46	58.35	37351.92
X3	568.19	745	17.05	5814.15
Input prices:				
P1	0.86	0.87	0.12	8.01
P2	0.03	0.02	0.01	0.15
P3	0.74	0.59	0.14	6.62
Outputs:				
Y1	62289.21	89296.15	2027.25	591355.8
Y2	36546.08	54105.02	158.15	421358.8
Y3	24691.61	38592.23	17.55	340015.6
Risk terms:				
Z1	8718.68	11095.79	195.47	79422.41
Z2	495.12	1056.44	2.14	14553.46
Z3	933.49	1863.85	0.14	18554.78
Total costs:				
TC	4399.14	6504.57	106.09	49422.49

All values are expressed in millions of CNY.
where X1: Personnel Expenses, X2: Total Interest Expenses, X3: Other Operating Expenses, P1: X1 / Total Assets, P2: X2 / Average Customer Deposits, P3: X3 / Total Assets, Y1: Gross Loans, Y2: Other Earning Assets, Y3: Loans and Advances to Banks, Z1: Equity, Z2: Loan Loss Provision, Z3: Non-performing Loans, TC: X1+X2+X3.

Source: Author’s own calculations

Table 4.8: Descriptive statistics of variables selected for equation (4.13) of sample rural commercial banks.

Variables	Mean	Std. Dev.	Min	Max
Inputs:				
X1	803.68	783.72	27.3	3517.09
X2	2629.17	2666.85	190.85	12649
X3	505.25	384.31	67.91	1662.29
Input prices:				
P1	0.74	0.36	0.10	2.16
P2	0.03	0.01	0.01	0.07
P3	0.55	0.24	0.20	1.46
Outputs:				
Y1	60841.34	47784.55	8415.93	192997.1
Y2	28272.93	30311.37	471.65	145568.8
Y3	23101.07	30823.73	611.12	178281.7
Risk terms:				
Z1	8807.27	7396.52	901.30	32941.37
Z2	457.16	440.30	3.72	2086.06
Z3	1171.23	1444.10	81.83	8373.67
Total costs:				
TC	3938.11	3712.89	352.5	15434.51

All values are expressed in millions of CNY.
where X1: Personnel Expenses, X2: Total Interest Expenses, X3: Other Operating Expenses, P1: X1 / Total Assets, P2: X2 / Average Customer Deposits, P3: X3 / Total Assets, Y1: Gross Loans, Y2: Other Earning Assets, Y3: Loans and Advances to Banks, Z1: Equity, Z2: Loan Loss Provision, Z3: Non-performing Loans, TC: X1+X2+X3.

Source: Author's own calculations

Table 4.9: Descriptive statistics of variables selected for equation (4.13) of sample foreign commercial banks.

Variables	Mean	Std. Dev.	Min	Max
Inputs:				
X1	371.11	435.48	0.4	1762.16
X2	839.88	939.87	1.2	4616.84
X3	292.13	345.29	0.5	1672.66
Input prices:				
P1	5.65	5.80	0.18	41.74
P2	0.04	0.02	0.01	0.16
P3	4.67	5.36	0.09	42.05
Outputs:				
Y1	22726.47	23617.17	71.1	118678
Y2	7039.79	12451.46	0.17	87849.03
Y3	10869.06	10273.55	17.76	45651.9
Risk terms:				
Z1	4584.71	4392.28	41.9	28288.92
Z2	121.96	204.15	0.14	1065.24
Z3	196.24	280.74	0.28	2128.22
Total costs:				
TC	1503.13	1604.51	2.1	7091.27

All values are expressed in millions of CNY.
where X1: Personnel Expenses, X2: Total Interest Expenses, X3: Other Operating Expenses, P1: X1 / Total Assets, P2: X2 / Average Customer Deposits, P3: X3 / Total Assets, Y1: Gross Loans, Y2: Other Earning Assets, Y3: Loans and Advances to Banks, Z1: Equity, Z2: Loan Loss Provision, Z3: Non-performing Loans, TC: X1+X2+X3.

Source: Author's own calculations

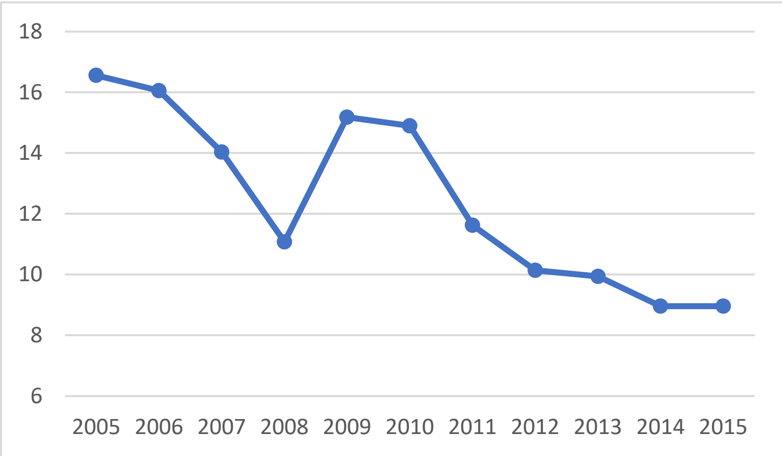
4.5 Empirical Results

4.5.1 Shadow Return on Equity and the Rank Order Correlation Test

During the past few decades, recapitalisation has taken place in the Chinese banking sector, attempting to redress banks' undercapitalisation as well as to satisfy the regulatory capital requirements (Hou et al., 2018). Therefore, it is of significance to analyse the effects of recapitalisation on Chinese banks over the sample period. Accordingly, as was pointed out in section 4.2, one of the intentions of this chapter is to investigate such effects by examining shadow return on equity (i.e., shadow price of equity). The shadow return on equity, $SROE_{it}$, is estimated through equation (4.19) and the evolution of $SROE_{it}$ across the sample period is presented in Figure 4.2. What we observed during 2005-2006 was that sample banks were highly leveraged towards debt financing and underused their equity capital relative to what might be deemed prudent. Such practices drove $SROE_{it}$ to a level which seemed fairly high relative to the market price of equity at this time. This might imply a relaxing regulatory environment for the Chinese banking sector or simply excessive risk-taking by Chinese banks.

The bank recapitalisation mentioned above led to an overall decrease in $SROE_{it}$ over 2005-2015, indicating improved competitive conditions and reduced funding costs in the Chinese banking market. However, during the crisis period, 2008-2009, the increase in the central bank's interest rate and funding costs induced a temporarily increase in $SROE_{it}$, when banks were willing to pay more to boost their capital levels. Overall, across 2005-2015, the sample bank adjusted from an equilibrium position of high leverage to another with low leverage, a pattern consistent with increasing utilisation of equity capital. In addition, during this process, our results suggest that Chinese banks were not confronted with significant short-run adjustment costs, as no negative values are generated for $SROE_{it}$. As suggested by Dong et al. (2016), negative shadow prices of equity emerge when the short-run deleveraging adjustment imposes significant costs on banks. Fethi, Shaban and Weyman-Jones (2012) also point out that banks whose present equity holding is much higher than their respective long-run equilibriums are expected to realise low or negative shadow prices of equity. Nevertheless, Figure 4.2 shows that the sample banks did not experience these patterns.

Figure 4.2: Evolution of shadow return on equity estimates (%).



Shadow return on equity is estimated by equation (4.19).

Source: Author's own calculations

Having discussed the results of shadow return on equity, next, the estimation findings of the Spearman's rank-order correlation test are analysed. As mentioned in section 4.4.1b, Spearman's rank-order correlation test (Spearman's rho) is employed for testing the relations between two sets of bank rankings. That is, our study constructs sample banks' ranking number in terms of their respective estimated scale inefficiency scores across each sample year and for both estimates obtained from the seemingly unrelated regression and SFA model. The correlations of these two sets of rankings – one is based on scores yielded from the regression in Chapter 3 and the other one is built upon scores produced from SFA in this chapter – then are tested using Spearman's rho[153]. The objective is to assess whether bank rankings generated by the two different modelling techniques are similar. If not, the policy conclusions proposed in

[153] The scale inefficiency scores yielded from seeming unrelated regression are offered in Table 3.16 on page 147 of Chapter 3, and scale inefficiency scores obtained by equation (4.22) from the stochastic cost function in this chapter are presented in Table 8.1 in Appendix B. Since Chapter 3 comprehensively analyses the scale economies and scale efficiency of Chinese banks, in this section we focus on the discussion of Spearman's rank-order correlation test results to examine whether the two different models rank banks similarly.

Chapter 3 will be fragile and model dependent. To the best of our knowledge, no Chinese banking empirical studies have practised this examination to check the consistency of estimations.

Spearman's rho approach is preferred to the standard Pearson product-moment correlation since it produces ranked (ordinal) data rather than actual inefficiency values. Essentially, the non-parametric adaptation of the Pearson correlation coefficient is Spearman's correlation coefficient, which is proxied by r_S (or ρ), quantifying the direction and strength of the linkage between two non-parametric variables (Wang, Wang and Wang, 2019). It is used to measure potential monotonic associations when a data-set's distribution does not meet the preconditions for the use of Pearson's correlation coefficient. It allows us to evaluate the relationship between two ranked variables through an arbitrary monotonic function and no assumption about the distribution is required (Borkowf, 2000). Overall, Spearman's rho has the advantages of being non-parametric, rank-based and size-independent, and, moreover, is more efficient in analysing large samples, as in the present case. Furthermore, with the help of bootstrapping method, our study accommodates the challenging statistical issue of there being no explicit formulas for finite sample variance estimation within the Spearman's rho approach (Gaißer and Schmid, 2010).

Table 4.10 presents the test results (including 95% confidence intervals). A feasible correlation is seen between the bank scale inefficiency rankings produced by the two different models. The correlation coefficients are all significant at the 1% level, and all are positive throughout the observation period. Its values range from a minimum of 0.53 in the year 2005 to a maximum of 0.93 in the year 2015, with the full sample giving a fairly strong positive correlation at the level of 0.91 over the whole sample period. Moreover, there is less variation in the values as the study period progresses. Thus, a certain consistency is identified between the seemingly unrelated regression and SFA; in general, these two models function in a consistent manner and rank Chinese banks in a comparable way. These results indicate the robustness of the estimations performed in Chapter 3.

Table 4.10: The rank-order correlation of two sets of scale inefficiency scores.

Year	Number of observations	Coefficient	IB_BCA	UB_BCA
2005	20	0.532***	0.194	0.863
2006	21	0.724***	0.331	0.941
2007	37	0.740***	0.506	0.905
2008	55	0.869***	0.796	0.945
2009	58	0.902***	0.744	0.961
2010	71	0.868***	0.794	0.922
2011	86	0.894***	0.819	0.930
2012	98	0.893***	0.844	0.925
2013	97	0.897***	0.853	0.941
2014	108	0.930***	0.882	0.949
2015	99	0.931***	0.896	0.956
Full Sample	750	0.907	0.890	0.923

****Correlation is statistically significantly different from zero at the 1% level*
IB_BCA: Lower bound of 95% bias-corrected confidence interval, UB_BCA: Upper bound of 95% bias-corrected confidence interval (on 1000 replications).

Source: Author's own calculations

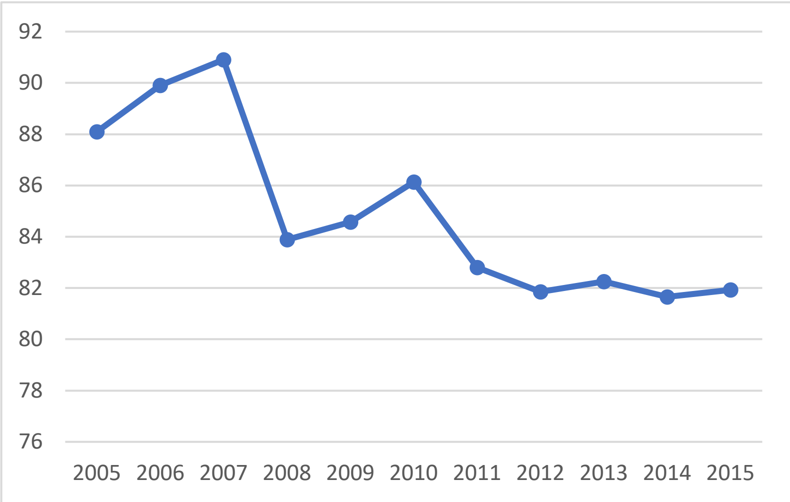
4.5.2 Cost Efficiency Estimation

The cost efficiency estimation passes all pre- and post-estimation tests – the skewness test on OLS residuals, M3T test (-10.85), and likelihood ration test (102.05) – and hence confirms the validity of our stochastic frontier cost function (4.13)[154]. Overall, the mean cost efficiency score of the full sample of banks over the full sample period, 2005-2015, is about 84.9%, which means Chinese banks were able to reduce costs by approximately 15.1% while still maintaining the same output vector. Specifically, as shown in Figure 4.3, from 2005, sample banks experienced a general improvement in their cost efficiency performance up until the start of the GFC: their cost efficiency score increased from 88.1% in 2005 to 90.9% in 2007. This finding is in line with Dong et al. (2014) and Hou et al. (2018), who also find an enhancement of the cost performance of Chinese banks within the same time interval[155].

[154] The parameter estimates obtained for the cost specification (4.13) are presented in Table 8.2 in Appendix B.

[155] Dong et al. (2014) hold the view that the improved macroeconomic environment, the accession into

Figure 4.3: Evolution of cost efficiency scores (%).



Cost efficiency scores are estimated through equations (4.13) and (4.14) by the Battese and Coelli (1995) model.

Source: Author's own calculations

After a period of growth, the efficiency score declined sharply in 2008, which could be a reflection of the worsened cost performance of sample banks during the GFC. The bad luck hypothesis might explain this decline. This hypothesis, proposed by Berger and DeYoung (1997), posits that deteriorating macroeconomic conditions arising from an unexpected exogenous shock (in this case is the GFC) can lead to an increase in the number of non-performing loans. Banks are then confronted with additional managerial costs as they try to improve their monitoring of loans[156]. After 2008, a short period of recovery is seen for sample banks, as the mean efficiency estimate rose from 83.9% in 2008 to 86.1% in 2010. However, the situation worsened again

WTO, and the opening up of the Chinese banking market (allowing the entrance of foreign banks and foreign transactions) significantly enhanced Chinese banks' efficiency during the pre-crisis period. Hou et al. (2018) attribute this increase in cost efficiency to bank credits having expanded rapidly in China during the period 2005 to 2008. For instance, more loans were issued with the strengthening capital position of banks and the opening of more bank branches. In these circumstances, Chinese banks strived to reduce their operational expenses while improving their management efficiency to handle the intensified competition in the market.

[156] Esho (2001) provides strong evidence in favour of the bad luck hypothesis for a dataset from Australian banks for the years 1985-1993. Rossi, Schwaiger and Winkler (2009), Chiu, Chen and Bai (2011) and Ghosh (2018) also offer evidence to support this hypothesis on Austrian banks over 1997-2003, Taiwanese banks during 1998-2002 and banks from 12 countries in the Middle East and North Africa over the period 2001-2012, respectively.

thereafter: there was a roughly 5% reduction in the levels of cost efficiency over 2010-2012. Then, between 2013 and 2015, bank cost performance was maintained at a relatively low yet stable level.

The bad management hypothesis, also developed by Berger and DeYoung (1997), may explain the low levels of cost efficiency of sample banks after 2010. That is, managers with poor credit management skills are less likely to be adept at credit scoring and tend to invest in projects with low or negative net present values. Besides, poor managers exhibit a lack of control over operating costs and show inadequate control over the credit monitoring process (loan portfolios are not adequately monitored and loan agreements are not enforced). Banks' loan loss provisions intend to increase under weak in practices after a lag (this tendency is demonstrated by the increase of loan loss provisions over 2010-2015 in our case – see Figure 3.3), which translates into reductions in the levels of cost efficiency among Chinese banks[157].

To deepen our investigation, sample banks are grouped on the basis of asset size to further examine cost efficiency[158]. Table 4.11 displays the estimates of cost efficiency for the sample banks in each asset group for each year. The table shows that asset group 3 has the largest mean value of cost efficiency (86.43%) among the 4 asset groups, implying that these medium-large banks on average are the most cost-efficient banks in the sample. During the sample period, it can be observed that banks in asset group 4 yielded fairly close cost efficiency scores as banks in asset group 3. The mean of cost efficiency for this group of largest banks is 86.22%. This higher level of cost efficiency for banks in asset group 4 relative to banks within asset groups 1 and 2 could be because they obtain subsidies and favourable treatment from the government (Wheelock and Wilson, 2012; Zha et al., 2016). Furthermore, these larger banks are considered to be

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[157] The bad management hypothesis is supported by Williams (2004) for European savings banks over 1990-1998, Podpiera and Weill (2008) for Czech banks during 1994-2005, Louzis, Vouldis and Metaxas (2012) for Greek banks over 2003-2009, and Chaibi and Ftiti (2015) on a cross-country panel of French and Germany banks over 2005-2011.

[158] See Table 3.17 for the classification of asset size groups. To recap, asset group 1 are the sample banks in the lowest quartile (banks with the lowest average asset size) and asset group 4 are the sample banks in the highest quartile (banks with the highest average asset size).

protected by implicit government guarantees and hence are more likely to be capable of attracting funds even when paying lower interest rates (on borrowing) than other smaller banks.

Concerning the banks in asset group 2, these medium-small banks enjoyed high levels of cost efficiency as those banks in asset groups 3 and 4 up until the start of the GFC. Then, their efficiency score declined substantially from 90.29% in 2008 to 81.7% in 2015. Asset group 1, containing those smallest banks, produces the smallest mean efficiency score (82.44%) among the 4 size groups, and thus is the group with the worst practice. Indeed, noticeable efficiency variations are witnessed between this asset group and groups 3 and 4 (see Table 4.11). Such findings are in accordance with what has been reported by Zha et al. (2016), where largest commercial banks were found to be able to achieve greater cost economies than their smaller counterparts in a sample of Chinese banks. Nevertheless, across the sample period of 2005-2015, asset group 4 is the only one to exhibit an overall upward trend in cost efficiency estimates (its score rose by nearly 31% from 63.41% to 82.88%), while a gradual yet fluctuating downward tendency is seen for the other three groups.

Having analysed above the estimation findings based on four asset groups, we now compare the cost efficiency of different types of Chinese banks. Table 4.12 gives the cost efficiency estimates obtained for sample banks in each type at each tested year. As shown, on average, foreign commercial banks are the most cost-efficient, with a mean efficiency score of 87.08%, followed by rural commercial banks (86.4%), joint-stock commercial banks (85.94%), city commercial banks (85.29%) and state-owned commercial banks (79.74%). Indeed, in our sample, foreign commercial banks are the best practice banks that define the efficiency frontier. The high cost efficiency levels achieved by this type of banks could be a result of superior managerial expertise, governance and technology. Our findings are in line with prior work, such as Berger, Hasan and Zhou (2009), Matthews (2013) and Dong et al. (2016). These studies suggest that the more mature operations and a more relaxed regulatory environment of foreign banks relative to domestic banks allow them to more efficiently spread costs over their outputs.

Regarding the rural commercial banks and city commercial banks, the key driver that supports the superior cost performance of these two types of banks could be the increased competition within their specific bank segments. Across the sample period, we find that the cost efficiency estimates produced for city commercial banks and rural commercial banks are roughly similar (see Table 4.12). To illustrate, city commercial banks record a mean of 85.67% for cost efficiency score in 2005, and the yearly cost efficiency score for rural commercial banks is 86.44% in 2005. There is only a 0.89% difference between these two scores. Similarly, year 2008 reports a 0.33% difference and a 0.19% difference is observed in year 2011. However, the dispersion in the levels of cost efficiency between these two types of banks has been increasing since 2011, alongside the overall reduction in cost efficiency scores for both types. The mean cost efficiency score for rural commercial banks is 84.25% in 2015, a decrease of about 3% from 86.44% in 2005. City commercial banks' mean efficiency estimate declined noticeably from 85.67% to 80.14% over 2005-2015.

Compared with state-owned commercial banks, joint-stock commercial banks are able to realise much higher levels of efficiency gains during the tested period. This better cost performance of joint-stock commercial banks confirms the general expectation that joint-stock banks outperform state-owned banks as they have no historical NPL burdens as in state-owned banks and better risk management practices, and are subject to less government interventions (see, Ariff and Can, 2008; Berger et al., 2009; Hou, Wang and Li, 2014; Pessarossi and Weill, 2015; and Dong et al., 2016). Nevertheless, our results are contrary to Dong, Hamilton and Tippett (2014) whose study finds that state-owned banks are the winners in comparison to joint-stock banks in attaining cost efficiencies in China. Differences in such results may be due to different input-output mix, methodologies, and particularly different periods being analysed. An interesting point worth noting is that joint-stock commercial banks have the largest variations with regard to cost efficiency in the sample.

As for the worst player in the banking market, Chinese state-owned commercial banks, on average, they are around 8% less cost-efficient than the best practice banks – foreign commercial banks. The huge restructuring costs (a result of banks' choice of active merger and acquisition responding to the GFC) and massive expenses which related to the previous misconduct instances may explain the low efficiency levels generated by state-owned commercial banks. Moreover, their cost performance can be burdened with additional capital regulations due to the 'too big to fail' incentive (Schmaltz et al., 2014). Yet, these banks might benefit from the fintech or e-banking initiatives, giving rise to recent improvements in their cost efficiencies. Table 4.12 presents that their cost efficiency score increased from 75.75% in 2005 to 80.81% in 2015. Such findings are in accordance with the results documented in Huang and Fu (2013), where enhancements in cost efficiency were found for Chinese state-owned banks, which was attributed to the intense competitive pressure forcing these banks to be more efficient by upgrading technologies and operating on market principles.

Table 4.11: Estimated cost efficiency scores in each asset size group.

Year	**Asset group 1**	Std. error	**Asset group 2**	Std. error	**Asset group 3**	Std. error	**Asset group 4**	Std. error
2005	63.41%	0.079	85.71%	0.011	85.46%	0.012	86.66%	0.010
2006	88.59%	0.017	89.10%	0.008	87.67%	0.008	88.89%	0.007
2007	90.83%	0.004	90.35%	0.010	89.71%	0.007	90.17%	0.005
2008	91.07%	0.006	90.29%	0.012	91.70%	0.003	91.80%	0.005
2009	79.58%	0.027	85.90%	0.013	87.67%	0.008	85.04%	0.023
2010	81.03%	0.036	84.36%	0.015	88.27%	0.008	86.59%	0.022
2011	84.94%	0.021	85.36%	0.010	88.17%	0.006	88.16%	0.011
2012	82.07%	0.022	82.62%	0.011	84.94%	0.014	84.33%	0.012
2013	81.42%	0.025	79.70%	0.015	83.00%	0.013	83.28%	0.011
2014	81.05%	0.023	82.37%	0.010	83.17%	0.009	82.42%	0.010
2015	82.88%	0.012	81.70%	0.012	80.94%	0.016	81.08%	0.011
Full sample	82.44%	0.008	85.22%	0.004	86.43%	0.004	86.22%	0.004

Cost efficiency scores are estimated through equations (4.13) and (4.14) by the Battese and Coelli (1995) model.
See Table 3.17 for the classification of asset size groups.

Source: Author’s own calculations

Table 4.12: Estimated cost efficiency scores of different types of banks.

Year	**State-owned**	**Joint-stock**	**City**	**Rural**	**Foreign**
2005	75.75% (0.038)	85.80% (0.019)	85.67% (0.007)	86.44% (0.026)	80.75% (0.099)
2006	79.50% (0.018)	91.56% (0.008)	88.04% (0.007)	87.56% (0.014)	89.36% (0.029)
2007	81.06% (0.025)	89.72% (0.030)	90.62% (0.002)	88.51% (0.011)	91.73% (0.007)
2008	77.89% (0.016)	91.64% (0.004)	90.97% (0.003)	90.67% (0.008)	91.68% (0.018)
2009	79.50% (0.013)	80.95% (0.070)	84.17% (0.013)	86.66% (0.015)	88.25% (0.012)
2010	81.06% (0.008)	81.41% (0.090)	86.06% (0.010)	86.17% (0.014)	85.13% (0.034)
2011	77.89% (0.007)	89.45% (0.011)	86.07% (0.009)	86.24% (0.008)	89.78% (0.007)
2012	81.20% (0.044)	84.73% (0.019)	82.95% (0.007)	85.06% (0.007)	87.24% (0.010)
2013	81.87% (0.019)	84.24% (0.014)	81.84% (0.007)	84.70% (0.007)	85.34% (0.011)
2014	80.61% (0.012)	84.31% (0.022)	81.67% (0.001)	84.09% (0.011)	84.26% (0.020)
2015	80.81% (0.008)	81.47% (0.019)	80.14% (0.027)	84.25% (0.008)	84.31% (0.012)
Full sample	79.74% (0.021)	85.94% (0.008)	85.29% (0.003)	86.40% (0.003)	87.08% (0.006)

Cost efficiency scores are estimated through equations (4.13) and (4.14) by the Battese and Coelli (1995) model. Standard errors are in parenthesis.
State-owned: state-owned commercial banks, Joint-stock: joint-stock commercial banks, City: city commercial banks, Rural: rural commercial banks, Foreign: foreign commercial banks.

Source: Author's own calculations

Having reviewed the overall trend of cost efficiency of sample banks, we now move on to the analysis of the determinants of cost inefficiency. As specified in equation (4.14), our efficiency estimation is subject to the constraints of exogenous variables included in the cost function. Table 4.13 below displays the empirical findings of the effects of these exogenous factors on inefficiency. With respect to PGR_t, a negative correlation (-0.001) is observed between this ratio and cost inefficiency, suggesting inefficiency reduces as PGR_t increases. Indeed, the stronger income-generating ability of state-owned firms improves their debt-servicing capacity, which in turn strengthens the credit quality of banks. More cost savings can be realised in this case since banks need to put less effort into managing their loans and enhancing their risk management practices. Nevertheless, the coefficient is statistically insignificant, which could be an indication that the interconnectedness between the performance of Chinese state-owned firms and the performance of Chinese banks is rather weak during the observation period.

$GDPGR_t$ is found to be significantly and negatively associated with cost inefficiency – a coefficient value of -0.063 is obtained (see Table 4.13). This result contrasts with what has been documented in several prior related studies, such as Bushman and Williams (2012), Bryce et al. (2015) and Diallo (2018), where a positive correlation is reported between $GDPGR_t$ and cost inefficiency. However, our finding is in line with Chan and Karim (2010), who suggest that higher economic growth usually results in a more competitive and mature environment that translates into managerial efficiency and operational cost savings for banks. That is, in the context of a fast-growing economy, banks tend to be more efficient in acquiring strong cash flows and customer deposits and thereby enhance their efficiency. Moreover, public savings and company profits could benefit from a rapidly expanding economy, and so borrowers will be more likely to be able to make repayment on time, easing the credit risk profile of banks and promoting management efficiency (Pessarossi and Weill, 2015).

Interestingly, INF_t yields a statistically insignificant coefficient, meaning that variation in cost inefficiency is not related to variation in inflation amongst sample banks during 2005 to 2015. With respect to IR_t, a positive coefficient (0.056) is obtained at the 1%

significance level, indicating that a higher interest rate leads to cost inefficiencies in the Chinese banking industry (see Table 4.13). Table 4.3 shows that IR_t surged from -1.47% in 2011 to a high level of 4.73% in 2014, before decreasing thereafter. China's inconsistent monetary policy, which repeatedly loosened then tightened the money supply, which have worsened banks' level of bad debts. That is, commercial banks had higher operating costs, in the form of greater loan loss provisions. This fits the bad luck hypothesis introduced above. Similar findings have been reported by Rossi, Schwaiger and Winkler (2009), Chiu, Chen and Bai (2011) and Niţoi and Spulbar (2015). In general, they assume that a higher interest rate is associated with an increase in debt burdens for borrowers and then might cause the increase of the probability of default on their loans.

Table 4.13 shows that ER_t was associated with increases in inefficiency of sample banks over 2005-2015, demonstrated by a significantly positive coefficient of 0.539. Indeed, the depreciation of the CNY encouraged the development of export industry, which indirectly expands the demand for bank credits in the economy. As Maudos et al. (2002) suggest, banks in an expanding market usually exhibit lower levels of cost efficiency because they are less motivated to control their costs. Another significant aspect of the effects of ER_t is that the depreciation of CNY hurts the asset quality of domestic borrowers and the nation's real economy. In response, banks' NPLs are likely to pile up, and hence banks become less cost-efficient as they have to spend more on monitoring loans and on subsequent collateral revaluation. Importantly, expenses may arise when negotiating possible restructuring agreements with borrowers (Bruno and Shin, 2015).

A similar proposition can be seen in Eichler and Littke (2018). They further argue that changes in the exchange rate can cause changes in a bank's balance sheet in terms of composition and total value, which in turn heighten the uncertainty of bank operation and further increase concerns about exchange rate risk. Consequently, the bank might encounter higher costs to strengthen its risk management practices, especially the capacity to hedge potential exchange rate risk. Besides, they point out that the appreciation of the domestic currency could be beneficial for bank cost performance if it is motivated by the nation’s economy becoming more competitive and productive.

Table 4.13: The estimation results of determinants of cost inefficiency.

	Coefficient	Standard Error	z	P>z
PGR_t	-0.001	0.001	-1.360	0.175
$GDPGR_t$	-0.063	0.015	-4.270	0.000
INF_t	-0.006	0.006	-1.060	0.288
IR_t	0.056	0.014	4.000	0.000
ER_t	0.539	0.141	3.830	0.000
Constant	-0.494	8.449	-0.010	0.195

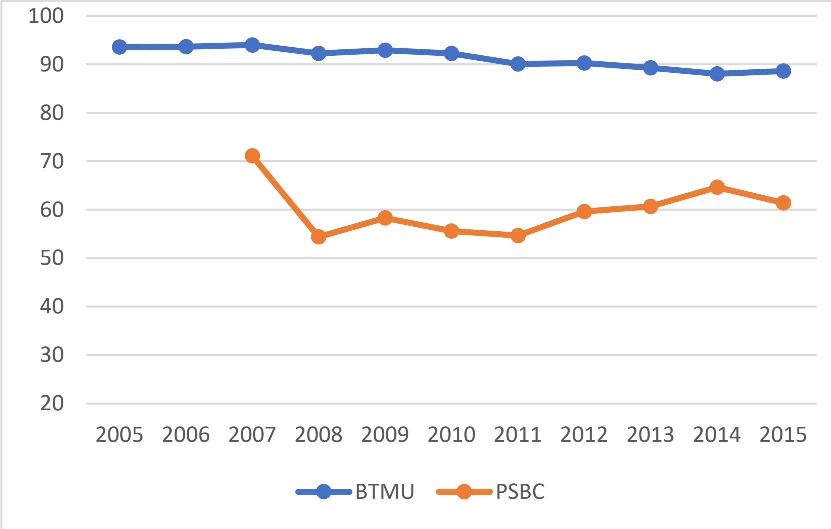
PGR_t: annual growth rate of industrial profits (%), $GDPGR_t$: national annual GDP growth rate (%), INF_t: national annual inflation rate (%), IR_t: national annual real interest rate (%), ER_t: national annual exchange rate against US dollar. These are the five exogenous variables specified in equation (4.14) and parameter estimates were obtained by the Battese and Coelli (1995) model.

Source: Author’s own calculations

Interestingly, one bank in the study sample consistently performed better than the others in most of sample years, with an average cost efficiency level of 91.3%. This bank is the Bank of Tokyo Mitsubishi UFJ (China) (BTMU). Figure 4.4 shows that the BTMU operated efficiently throughout the sample period, with little variation in its cost efficiency. Its parent bank, the Bank of Tokyo Mitsubishi UFJ (Japan), started to collaborate with the Chinese banking sector from 1958 and has been actively engaged in supporting Chinese business since then. It launched its first headquarters in Shanghai in 2004 and was the first established foreign bank (100% controlled by the parent bank) in China after the market opened. As a foreign bank, its excellent cost performance supports the proposal, developed in Berger et al. (2009), Matthews (2013) and Dong et al. (2016) on the basis of empirical results, that joint-stock and foreign banks normally lie close to the frontier of efficiency[159].

[159] Further support for this proposal is given by the study results in that the next most cost-efficient bank in the sample is the South Korea Hana Bank (China).

Figure 4.4: Evolution of cost efficiency scores for BTMU and PSBC (%).



BTMU: Bank of Tokyo Mitsubishi UFJ (China), PSBC: Post Savings Bank of China; cost efficiency scores are estimated through equations (4.13) and (4.14) by the Battese and Coelli (1995) model.

Source: Authors own calculations

These studies point out that a more relaxed regulatory environment, stronger financial innovations as well as more mature operations of foreign banks than domestic banks are the main contributions to the higher efficiency levels generated by foreign banks. These factors may also largely explain the higher efficiency gains experienced by BTMU throughout the observation period. For instance, BTMU may profit from its better risk management practices and reliance on modern information technologies. For example, BTMU follows its parent bank in employing an advanced non-performing loans recovery regime to manage its risk profile and minimise costs. In 2012, its top ten clients (mainly Japanese listed firms or joint venture corporations) accounted for over 38% of its total lending and the bank had recovered almost 42.73% of these corporate loans by the end of the third quarter of 2012 (BTMU annual report, 2012).

Moreover, as a wholly controlled foreign bank, BTMU is less subject to domestic credit allocation rules (e.g., 'lending quota'[160]), which could enable the bank to allocate its

[160] The 'lending quota' had significant effects on Chinese banks during its period of implementation, 1995-2015. According to the PBOC (2001), the lending quota (or loan quota) was issued by the PBOC or State Council via a set of mandatory indexes to impose an upper limit to the lending capacity of

resources more freely and efficiently than domestic banks. The high levels of cost efficiency produced by BTMU could be a result of superior managerial skills or best-practice procedures, or of obtaining diversification of risks that permits higher-risk investments with higher expected returns. In contrast, the Post Savings Bank of China (PSBC)[161], as one of the largest state-owned banks in China, was a poor performer over the study period, with an average cost efficiency level of 63.3%. This bank specialises in supporting small business (microfinance) and rural areas, where, until recently, the only alternative was putting money under the mattress! It started with an extensive network of over 40,000 branches, covering almost all regions of China, with many of them in rural areas, to provide basic financial services to its more than 600 million low-income retail customers (Postal Savings Bank of China, 2019).

Indeed, since its establishment, PSBC has been expanding its business in rural areas in China with the aim of improving the unbanked and underbanked situation in these areas. This carries substantial operating costs, such as higher personnel expenses, for the bank (CBRC, 2015). Also causing inefficiencies, a poor technological capability of the PSBC has likely restricted its ability to efficiently monitor and allocate its resources. Furthermore, Lin and Zhang (2009) point out that the credit allocation of state-owned banks in China seems to be unavoidably affected by the pervasive nature of state control and bank efficiency could be limited by potential conflicts of interest between the state as a major shareholder and as regulator. Yet, these banks may benefit from Fintech or e-banking initiatives, giving rise to recent improvements in their cost performance.

Chinese banks. Specifically, the central bank released quarterly and annually maximum amounts of each type of loan that could be issued by banks. In total, the quota capped lending at 75% of the bank's balance of deposits. All banks had to align with this regulation and banks were prohibited from exceeding the set limits or diverting balances across different loan types, except with the approval of the PBOC. However, the PBOC relaxed this mandatory requirement for foreign banks (Zhang, Wang and Wang, 2012). For example, the upper limit of the proportion of corporation loans and real estate loans over total loans were higher for foreign banks than for domestic banks.

[161] The PSBC is a young commercial bank, established in 2007 from the transformation of the earlier Post Savings Credit Cooperative, which was owned by the State Post Bureau.

4.5.3 Determinants of Bank Profitability

4.5.3a The Baseline Regression

This section discusses the empirical findings of the baseline profitability equation (4.2). An overview of post-estimation diagnostics is offered first, followed by interpretations of obtained model results. Table 4.14 (column C) below displays parameter estimates from equation (4.2); the findings of the ordinary least squares and fixed effects model are outlined in the table as well, for comparison[162]. The rationale for including them to compare with system GMM estimation is addressed on page 175-176. As shown in Table 4.14, the lagged component ($SROE_{it-1}$) is highly significant in all three modelling approaches. More importantly, as expected, the coefficient for $SROE_{it-1}$ from GMM provides a robust result, as the GMM estimate (0.802, see column C) is higher than the FE estimate (0.416, see column B) and lower than the OLS estimate (0.863, see column A)[163].

Concerning the post-estimation diagnostics described in section 4.4.1a for system GMM, the baseline equation (4.2) satisfies all model requirements (see column C of Table 4.14). First, as for the instrument proliferation issue, the number of instruments employed (117) in the model is smaller than the number of groups (118) observed in the dataset. Second, the Hansen J-statistic of the overidentification test has a value of 0.618, which confirms that the instrumental variables (IVs) utilised in the estimation are valid (IVs are exogenously determined and not correlated with the model error

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[162] We also estimate equations (4.2)-(4.7) by the Ordinary Least Squares (OLS) estimator and Fixed Effect (FE) estimator. For OLS, the Breusch-Pagan test is performed to detect heteroskedastic residuals within the dataset. All model specifications reject the null of homoscedasticity assumption, implying that OLS estimators are biased and inconsistent because of the existence of heteroskedastic disturbances in the panel. The FE method, in this case, is preferred over OLS since it takes account of unobserved heterogeneity across panels (the Hausman test rejects the null and hence the fixed effect model is preferred over the random effect model for all model specifications). Nevertheless, the FE model is not capable of controlling sufficiently for endogeneity and suffers from the serious Nickell bias when a dynamic panel model is proposed (i.e., the inclusion of lagged terms); see explanations of the Nickell bias on page 176.

[163] In general, the OLS estimate of the coefficient on the lagged dependent variable is much more likely to be biased upward, while there tends to be a downward bias in the estimate of parameter value on the lagged component in the case of the FE specification (Arellano and Bond, 1991; Blundell and Bond, 1998 and Fukase, 2010). See specific explanations on page 176.

term). Third, the specification satisfies the difference-in-Hansen test (0.272), justifying our treatment of instrumentalising the lagged term by its own first lag. Moreover, the obtained result (0.486) for the difference-in-Hansen test for levels equation suggests the validity of the subsets of IVs used in it. Fourth, the model is free from serial correlation issues, given that AR (1) and AR (2) provide us with p values of 0.000 and 0.239 respectively.

The baseline model (4.2) passes all the estimation diagnostics – parameter estimates offer valid information for our profitability determinants analysis of the Chinese banking system. The lagged term, $SROE_{it-1}$, is found to be highly significant and has positive impacts on bank profitability, with a coefficient value of 0.802 (see column C of Table 4.14). That is, higher levels of profitability are expected for sample banks that displayed stronger earning capacities over the previous year, verifying our assumption about the dynamic nature of the panel in the model specification. Indeed, the significant and positive coefficient on $SROE_{it-1}$ demonstrates that the profitability of Chinese banks is persistent. Since surplus profits earned in highly competitive markets will not persist as new competitors are attracted (Goddard, Molyneux and Wilson, 2004), the profitability persistence in our case might be associated with the presence of impediments to competition within the Chinese banking industry, such as high entry barriers and government interventions.

This finding is in accordance with García-Herrero, Gavilá and Santabárbara (2009) whose study also finds profit persistence in the Chinese banking sector. Their paper analyses empirically the low profitability of 87 Chinese banks during 1997-2004 and points out that regulations prohibiting the entry of both domestic and foreign competitors should lead to the persistence of profitability among examined banks. Similar explanations can be seen in Athanasoglou, Brissimis and Delis (2008) in relation to the Greek banking sector. They suggest that the banking system is perceived to be highly competitive (showing a high speed of adjustment) if the coefficient value on the lagged component close to 0. A value close to 1 reveals a low speed of adjustment and a less competitive market structure. In our case, a coefficient of 0.802 indicates that bank profitability persists to a high extent and the Chinese banking industry is more than likely to have a weakly competitive market structure[164].

The coefficient on CE_{it} has a value of 0.152 (see column C of Table 4.14). This implies that higher profits are forecast for sample banks with higher cost efficiency scores, and that more cost-efficient banks are in a better position to allocate and utilise loanable resources (producing the same level of outputs from a lower level of inputs) compared with less efficient banks, thus enjoying greater profits due to cost savings. Increased cost efficiency scores imply better management quality of banks regarding optimal resource management in the production process and cost minimisation. In this regard, superior managerial competences could translate into profitability gains, a conclusion supported by several earlier empirical studies on bank profitability, including Pasiouras and Kosmidou (2007), Olson and Zoubi (2011) and Tan, Floros and Anchor (2017). A negative relation between costs and profits is documented in these studies. Looking at the magnitude of the impacts, banks' profitability is driven to a large extent by efficiency throughout the sample period. Accordingly, Chinese banks need to acquire superior risk management skills (to ensure, for example, that loan portfolios are sufficiently monitored and that greater credit quality is attained) to achieve greater cost efficiency in order to enhance profitability further.

$SHADOW_{it}$ has a negative but non-significant correlation (-0.009) (see column C of Table 4.14). One the one hand, shadow banking practices increase revenue diversification, and a well-diversified bank is able to achieve profit gains through better resource allocation via internal capital markets (Elsas, Hackethal and Holzhäuser, 2010), efficiency gains via economies of scope and reductions in idiosyncratic risk (Goddard, McKillop and Wilson, 2008). In addition, by circumventing strict capital requirements and liquidity constraints, shadow banking activities enhance banks' ability to minimise

[164] The history and structure of the Chinese banking system (see Chapter 2) suggests that the large state-owned banks have diminished market competitiveness and that the Chinese banking industry presents a relatively high concentration ratio compared with its main counterparts (see Figure 2.3). Yet, it should be noted that more competitive environment has been established recently thanks to a series of banking reforms as well as developments such as emergence of Fintech.

costs[165], shift regulatory burdens and reduce compliance costs[166] (Hou et al., 2018). Its growth stimulates new product innovations as well as technical innovations, which translates to competitive advantage, thereby again facilitating banks' ability to enhance their profitability.

On the other hand, these profit benefits come with costs. For the identified costs, Elsas, Hackethal and Holzhäuser (2010, page 2) cite "*agency problems[167] related to diversifying investments, an inefficient resource allocation problem due to malfunctioning of internal capital markets, an asymmetric informational problem due to miscommunication between head office and divisional managers and reckless rent-seeking attitude of managers*". Moreover, banks with a high percentage of shadow activities in their revenue streams may be less profitable as the revenues generated from these activities are commonly perceived to be more volatile than revenues from traditional banking activities (Ding, Fung and Jia, 2015).

Overall, the conflicting impacts on profitability could offset each other and result in the non-significant estimation of $SHADOW_{it}$ in our model. Our result shows that Chinese banks need to improve their competence in managing the intrinsic costs related to shadow banking activities to achieve profit increases.

Next, $SFTF_{it}$ significantly and positively determines bank profitability, with a coefficient of 0.051 (see column C of Table 4.14). Evidently, sample banks' profitability benefited from the utilisation of short-term wholesale funds over the observation period. First, this funding strategy largely diversifies funding resources for sample banks, it gives banks the advantage of obtaining more available financing to mature

[165] Hou et al. (2018) argue that banks need to redesign their internal management mechanisms in order to carry out shadow banking activities – giving banks the opportunity to reduce operational inefficiencies and hence boost cost efficiency.

[166] For instance, the acceptances and documentary credits (that considered in our estimation) are deemed to be off-balance sheet activities and hence are not counted against banks' core Tier 1 capital and so require lower common capital buffers against losses.

[167] The agency problem refers to the excessive risk-taking behaviours of bank managers to seek expansion via diversification in order to pursue personal gains, instead of maximising shareholders' returns.

their liabilities, meet client needs and fully exploit investment opportunities, which in turn contribute to higher levels of profitability in banks. Besides, better-diversified funding resources strengthen a bank's liquidity position (i.e. give it a lower probability of incurring liquidity risk) and therefore decrease the chances of bankruptcy. Ngalawa, Tchana and Viegi (2016) posit that banks with greater solvency send out positive signals to the market and thus have more and wider access to cheaper funds. Greater profitability is expected in this circumstance due to reduced funding costs. Second, given that short-term wholesale funds are normally classified as a risky financing option, the observed positive effects of $SFTF_{it}$ on profitability supports the belief that more lending leads to higher risk-taking and consequently enhanced profits.

Surprisingly, a non-significant positive coefficient (0.026) and a non-significant negative coefficient (-0.023) are produced for $T1_{it}$ and $NPLs_{it}$ respectively (see Table 4.14, column C), suggesting that bank profitability in China seems to be independent of capital strength and asset quality. Although our results indicate the effects of $T1_{it}$ and $NPLs_{it}$ are non-significant, the direction of those effects are in line with the findings of Zhang et al. (2016). Drawing on a sample of 87 Chinese commercial banks for the years 2006 to 2012, Zhang et al. (2016) argue that sufficient capital holding signals high creditworthiness of banks in the market, which in turn boosts profitability through lowered funding costs and that lower levels of non-performing loans indicate higher levels of profitability as less loan loss is charged against earnings. Accordingly, in their paper, the more profitable Chinese banks are those with adequate capital holding and less stock of non-performing loans on their balance sheets. The non-significant signs obtained in our model might suggest these favourable effects were exercised by sample banks only to a very limited extent over the study period[168].

$SIZE_{it}$ has significantly positive effects on bank profitability across the sample duration. As was pointed out in section 4.4.1a, $SIZE_{it}$ is included to capture any economies or diseconomies of scale in the market. Clearly, a significant positive

[168] Indeed, as discussed in Chapter 2, high burdens of non-performing loans and reductions in nearly all diverse earning sources due to depressed interest rates were the primary reasons for the deteriorations in profitability of Chinese banks.

coefficient of 0.159 (see column C of Table 4.14) shows that sample banks' profitability improves with the growth of size due to the cost savings generated through economies of scale. Furthermore, increase in size is associated with more diversified business models, funding resources and market segments (Loukoianova, 2008); therefore, larger banks tend to realise greater profits than smaller banks. Another explanation could be that huge banks commonly have large market shares and thus are able to earn supernormal profits by exercising market power in pricing their services and products (Varotto and Zhao, 2018).

To further explore the implications of $SIZE_{it}$ on profitability, its quadratic term is discussed. That is, we add a quadratic term – $SIZEsq_{it}$ – to the baseline regression (4.2) and the corresponding findings are specified in column D of Table 4.14, where a significant positive coefficient (0.115) signifies a parabola shape for its margin plot. Indeed, this convexity shows that the positive correlation between size and profitability holds only for sample banks whose size is above CNY587,029.29 million[169]. When a bank's assets are below this threshold, growth in size reduces bank profits. This non-linear relation fits our scale economies analysis of Chinese banks in the Chapter 3. That is, in section 3.5.3, sample banks are grouped into four quartiles in terms of their asset size for a comparative analysis (see Table 3.17). Our study finds that a further increase in size results in significant diseconomies of scale for banks in asset quartiles 1, 2 and 3, and only banks in quartile 4 see increasing returns to scale by further expansion (see Table 3.18)[170]. Accordingly, growth in size initially reduces profitability for sample banks with smaller asset size (asset size below CNY587,029.29 million) when further expansion in size lead to diseconomies of scale, and but increases profitability after a size threshold is reached. In this case, the policy recommendations that require the downsizing of large Chinese banks would induce economic costs for those banks in

[169] This value is calculated as $-3.056/(2 \times 0.115)$: see the coefficient values in column D of Table 4.14. The calculated value is -13.283. Since the logarithm values of $SIZE_{it}$ are utilised in the estimation, the un-log value of -13.283 indicates the original value of asset size is CNY587,029.29 million. Its 95% confidence interval is [228,205.09, 1510,573.59].

[170] As shown in Table 3.17, we divide the full sample into four quartiles according to asset size. To recap, the size range for quartile 1 is from 89.6 to 20,224.469; quartile 2 is from 20,227.371 to 49,584.623; quartile 3 is from 49,590.346 to 131,022.17; and quartile 4 is from 131,080.5 to 15,151,252 (all values are expressed in CNY million).

the form of forgone profits.

Table 4.14 (column C) shows that profitability is significantly and positively driven by PGR_t: the estimated coefficient is 0.044. This result confirms our assumption that stronger earning capacities of state-owned enterprises strengthen their debt-servicing abilities, and the resulting lower levels of doubtful loans and provisions for bad loans reduce banks' operating costs, which in turn boost profits. Within this context, Chinese banks need to sufficiently monitor borrowers' (state-owned enterprises) behaviours to ensure the quality of these loans in order to improve profitability. This is important for the Chinese banking industry considering that sizeable government-directed loans have been made to state-owned firms despite the fact that most of these firms operate with deficits (see Table 4.3).

We turn now to a discussion of the macroeconomic variables considered in the baseline model (4.2). As shown in column C of Table 4.14, except for IR_t, all the other macroeconomic variables have significant effects on profitability.

In particular, a coefficient of 0.327 shows that higher $GDPGR_t$ increases profitability. This can be interpreted as credit demand rising with cyclical upswings and thus boosting profitability. Furthermore, a booming real economy usually entails strengthened asset quality of banks, and the lower levels of loan losses and provisions for credit losses improve the revenues of banks. Wan (2018) and Simper, Dadoukis and Bryce (2019) advise that even during economic downturns managers can protect banks from the adverse effect of poor asset quality through income-smoothing behaviours, whereby banks may not be as severely affected as expected. Nevertheless, concerns about negative impacts also should be pointed out. For instance, there is evidence that stronger economic growth increases competition, which reduces bank profitability (see, Chan and Karim, 2010; Chronopoulos et al., 2015; and Partovi and Matousek, 2019). Such impacts should be minor amongst Chinese banks as China still has a relatively uncompetitive banking structure.

INF_t has an adverse effect on profitability, with a coefficient of -0.474 (see column C of Table 4.14) – the higher inflation is, the lower is profitability. This reflects the inability of sample banks to anticipate future inflation and hence they fail to make timely and appropriate adjustments to their interest rates. In addition, unexpected increases in inflation will give rise to cash flow difficulties for borrowers, which can lead to early termination of loan contracts and precipitate loan losses. When costs rise faster than generated incomes, bank profits will deteriorate (Bikker and Hu, 2002). Furthermore, according to Demirgüç-Kunt and Huizinga (2010), higher inflation induces credit rationing in banks, which in turn curbs their profitability. Moreover, as the coefficient on IR_t is not statistically significant, this variation in profitability is not related to the variation in interest rates.

Finally, ER_t is found to be negatively correlated with profitability, with a coefficient of -1.756, meaning that Chinese banks are exposed to foreign exchange risk. On the one hand, movements of the exchange rate can affect banks' trading revenues directly because of their foreign exposures (Sahminan, 2007). On the other hand, they indirectly impact on the margins of banks, even those that carry no exposures. The understanding is that the depreciation of domestic currency erodes banks' earning capacities. In the case of sample banks, they are likely to pile up substantial non-performing loans due to fluctuating exchange rates, which in turn curtail profitability. Moreover, the deterioration in profitability can be greatly multiplied by the simultaneous movement of interest rates with exchange rates, as indeed as experienced by Asian banks during the Asian Financial Crisis (Chang, Suardi and Chang, 2017).

4.5.3b The Extended Regressions

As previously stated, two extended profitability regressions are proposed – see equations (4.4) and (4.6). That is, to account for the significance of 'too big to fail', the dummy variable $TBTF_i$ and its interaction term with $T1_{it}$ are added into the baseline model (4.2) to give equation (4.4). Another set of macroeconomic variables, $CAPGDP_t$, $SHIBOR_t$, $ALIBOR_t$ and $AGDPGR_t$, are added to the baseline regression (4.2) to allow equation (4.6) to perform a thorough examination of environmental effects. The empirical results for equation (4.4) are outlined in column E of Table 4.14, while the findings of equation (4.6) are exhibited in column F of the same table. Both of these extended regressions are correctly specified and estimated according to the checking procedure. Specifically, the number of instruments used (92/79) in the estimation of models (4.4)/(4.6) is smaller than yet close to the number of groups (118) in the sample dataset. The robustness of the overall group and subsets of instruments employed in the models are confirmed by the Hansen J-statistic (0.462) and the difference-in-Hansen test (0.487 for the lagged dependent term and 0.220 for the levels equation) respectively for equation (4.4), and all IVs show no association with the error term. Similarly, the Hansen test statistic for over-identification restrictions gives a satisfactory p value of 0.392 for equation (4.6), confirming the joint validity of all IVs utilised in the estimation. Failure to reject the null at a p value of 0.590 (0.659) on the difference-in-Hansen test confirms that specified subsets of IVs are valid instruments for $SROE_{it-1}$ (levels equation). Furthermore, a p value of 0.001 of AR (1) and a p value of 0.462 of AR (2) suggest that the differenced error terms are not second order serially correlated in equation (4.4). Similarly, equation (4.6) is not burdened with serial correlation concerns given that the p value of the Arellano-Bond test for AR(1) is 0.000 and the p value for AR(2) is 0.304. Apparently, two extended profit specifications pass all post-estimation diagnostics, and it can be concluded that they offer robust estimations for our analysis.

Table 4.14 (column E) reports a negative but non-significant coefficient (-1.718) for the dummy variable $TBTF_i$, indicating the TBTF status does not affect the profitability of sample banks. For non-TBTF banks (dummy variable taking the value of 0), $T1_{it}$ has significant negative effects on profitability. Increasing the holding of T1 regulatory capital reduces bank profits amongst non-TBTF Chinese banks. Such reductions could result from the policy headwind. That is, high yields on risky assets (e.g., non-traditional banking activities) have been compressed for these banks – a result of the government's effort to limit systemic risk accumulation by tightening capital regulations

(Claessens, Coleman and Donnelly, 2018)[171].

With respect to the 15 Chinese TBTF banks (for the dummy variable takes the value of 1), the sum of the coefficient value on $T1_{it}$ (-0.101) and the coefficient value on the interaction term $T1_{it} * TBTF_i$ (0.399) reveals the effects of $T1_{it}$ on the profitability of these banks. The value of 0.298 (statistically significant at the 5% level) means that holding higher levels of regulatory capital improves the earning ability of TBTF banks – tightened Basel III capital requirements positively affect the profitability of Chinese TBTF banks. Our findings indicate that the impacts of regulatory capital on bank profitability depend on the TBTF status of banks – increases in capital requirements adversely affect the profitability of non-TBTF sample banks while boosting earnings of TBTF sample banks. Our research seems to support the concerns expressed in Filson and Olfati (2014) and Crabb (2018) that small banks[172] face greater challenges in complying with complex prudential rules compared with large banks. This put small banks at competitive disadvantage.

Table 4.14 (column F) shows that $CAPGDP_t$ is significantly and negatively correlated with bank profitability, with a coefficient of -0.033. Unlike the perception discussed in section 4.3.1 that the equity market and the banking market complement each other, our study reveals that enhancements of the equity market are likely to hamper banks' returns in China. To recap, as explained in section 4.3.1, a well-developed equity market is generally considered to be beneficial for bank profitability, as it lowers funding costs for banks (since other available funds can more readily be accessed from the market) and facilitates banks' control of their risks as more information on listed corporations can be acquired from the market (Pasiouras and Kosmidou, 2007 and Mirzaei, Moore and Liu, 2013). However, on the contrary, improvements of the equity market greatly diversify capital sources for Chinese firms and investors, consequently

[171] A similar argument is documented in Chen et al. (2017), who posit that equity capital is pricey and that increases in capital requirements negatively affect bank businesses, including the volume and cost of mortgage loans and wealth management products. This study reports that the growth of fee incomes from wealth management products has been substantially truncated in Chinese banks because of the regulatory tightening on such services.

[172] In terms of asset size and systemic importance within the nation's banking market.

decreasing bank lending and reducing profits (Leung, Schiereck and Schroeder, 2017). Furthermore, capital-intensive investments are typically correlated with higher return rates. To compete with such financial instruments to retain their clients, banks have faced increasing operational costs recently (Hou et al., 2018). The negative impacts of $CAPGDP_t$ on profitability arise when the aforementioned negative externalities outweigh the gains received through lowered funding costs.

With respect to $SHIBOR_t$, a significant negative correlation (-0.541, see column F of Table 4.14) is observed, showing that higher values of $SHIBOR_t$ weaken the earning capacity of sample banks through increased borrowing costs in the interbank market. In view of the magnitude of the parameter (-0.541), our result demonstrates that bank profitability was fairly sensitive to fluctuations in $SHIBOR_t$ in China during the sample period.

Next, as presented in Table 4.14 (column F), a positive coefficient is generated for $ALIBOR_t$ (1.699) and for $AGDPGR_t$ (0.042). While the estimated coefficient on $ALIBOR_t$ is significant at the 1% level, and the coefficient on $AGDPGR_t$ is non-significant (profitability is not affected by $AGDPGR_t$).

$ALIBOR_t$ is focused upon since the performance of Chinese banks are vulnerable to variations in funding costs. This aggregated interbank offered rate extracts the variance of each respective interbank rate of the proposed five economies via factor analysis and is used to explore how financial uncertainties in these economies could affect bank profitability in China via risk contagion[173] [174]. Contrary to the popular comprehension that lower financing costs lead to increased profitability, the positive coefficient suggests that profit gains on higher $ALIBOR_t$ from derivatives trading surpass the higher costs of borrowing. Indeed, our results confirm that international

[173] Please refer to footnote 142 for the construction of $ALIBOR_t$.

[174] To recall, the five economies are the US, UK, Europe, Japan and Hong Kong. These five are considered because the China Financial Stability Report (2016) posits that they are the five regions considered to have close connections with the Chinese banking sector through capital flows and interbank exposures over the past few decades.

banking markets affect the domestic banking market via financial contagion.

Table 4.14: Empirical findings for the proposed bank profitability specifications.

Explanatory variables	OLS – equation (4.2)	FE – equation (4.2)	GMM – equation (4.2)	GMM – adding SIZE quadratic	GMM – equation (4.4)	GMM – equation (4.6)
	A	**B**	**C**	**D**	**E**	**F**
$SROE_{it-1}$	0.863***	0.416***	0.802***	0.792***	0.645***	0.724***
	(0.021)	(0.041)	(0.056)	(0.079)	(0.097)	(0.108)
CE_{it}	0.129***	0.103***	0.152***	0.126**	0.031	0.179**
	(0.033)	(0.032)	(0.031)	(0.057)	(0.061)	(0.089)
$SHADOW_{it}$	-0.011**	0.009	-0.009	-0.006	-0.017	-0.002
	(0.004)	(0.006)	(0.010)	(0.017)	(0.014)	(0.014)
$SFTF_{it}$	0.036***	0.061***	0.051*	0.167***	0.120***	0.067
	(0.013)	(0.015)	(0.028)	(0.061)	(0.039)	(0.041)
$T1_{it}$	0.021**	0.006	0.026	-0.113**	-0.101**	-0.003
	(0.011)	(0.026)	(0.017)	(0.051)	(0.051)	(0.054)
$NPLs_{it}$	-0.031	-0.064**	-0.023	0.009	-0.030	-0.032
	(0.027)	(0.026)	(0.031)	(0.064)	(0.066)	(0.044)
$SIZE_{it}$	0.039	-2.013***	0.159*	-3.056*	-0.568**	0.024
	(0.045)	(0.362)	(0.090)	(1.791)	(0.266)	(0.104)
PGR_{t}	0.043***	0.022***	0.044***	0.043***	0.042***	0.029
	(0.007)	(0.007)	(0.007)	(0.010)	(0.009)	(0.027)
$GDPGR_{t}$	0.236*	0.481***	0.327**	0.413**	0.416***	1.094***
	(0.136)	(0.123)	(0.121)	(0.178)	(0.180)	(0.471)
INF_{t}	-0.463***	-0.815***	-0.474**	-0.302	-0.609***	-1.132**
	(0.172)	(0.165)	(0.194)	(0.204)	(0.190)	(0.443)
IR_{t}	-0.048	-0.338***	-0.093	0.008	-0.222*	-0.349
	(0.107)	(0.100)	(0.125)	(0.128)	(0.130)	(0.225)
ER_{t}	-1.384***	-2.274***	-1.756***	-2.429***	-1.886***	-7.641***
	(0.543)	(0.520)	(0.471)	(0.709)	(0.670)	(2.808)

$\_cons$	-3.626 (3.721)	34.165*** (6.973)	-4.894 (4.242)	23.503 (14.473)	19.454*** (7.271)	33.713 (21.858)
$SIZEsq_{it}$				0.115* (0.069)		
$TBTF_i$					-1.718 (2.236)	
$T1_{it} * TBTF_i$					0.399** (0.203)	
$CAPGDP_t$						-0.033*** (0.011)
$SHIBOR_t$						-0.541* (0.283)
$ALIBOR_t$						1.699*** (0.565)
$AGDPGR_t$						0.042 (0.554)
R-sq (overall)	0.848	0.189				
Breusch-Pagan	0.000					
Modified Wald test		0.000				
Number of IVs (groups)			117(118)	89(118)	92(118)	79(118)
Hansen-J-statistics			0.618	0.365	0.462	0.392
Difference-in-Hansen test ($SROE_{it-1}$)			0.272	0.468	0.487	0.590
Difference-in-Hansen test for levels equation			0.486	0.386	0.220	0.659
AR (1)			0.000	0.000	0.001	0.000
AR (2)			0.239	0.731	0.462	0.304

**Correlation is statistically significantly different from zero at the 10% level, **Correlation is statistically significantly different from zero at the 5% level, ***Correlation is statistically significantly different from zero at the 1% level. Standard errors are in parenthesis.*

$SROE_{it-1}$: the autoregressive term, CE_{it}: cost efficiency scores (%), $SHADOW_{it}$: bank shadow exposures to total assets ratio (%), $SFTF_{it}$: short-term funding to total

funding ratio (%), $T1_{it}$: Tier 1 regulatory capital ratio (%), $NPLs_{it}$: non-performing loans ratio (%), $SIZE_{it}$: natural logarithm of bank size, PGR_t: annual growth rate of industrial profits (%), $GDPGR_t$: national annual GDP growth rate (%), INF_t: national annual inflation rate (%), IR_t: national annual real interest rate (%), ER_t: national annual exchange rate against US dollar (%), $SIZEsq_{it}$: the quadratic term of $SIZE_{it}$, $TBTF_i$: the dummy variable that takes the value of 1 for the domestic systemically important banks and 0 for the remaining banks, $T1_{it} * TBTF_i$: the interaction term of $T1_{it}$ and $TBTF_i$, $CAPGDP_t$: market capitalisation to GDP ratio (%), $SHIBOR_t$: 3-month Shanghai interbank offered rate (%), $ALIBOR_t$: aggregated interbank offered rate of the US, UK, Europe, Japan and Hong Kong (%), and $AGDPGR_t$: aggregated national annual GDP growth rate of the US, UK, Europe, Japan and Hong Kong (%).

Column A shows the estimation result of the dynamic base model as in equation (4.2) through 0rdinary least squares approach, column B is the estimation result of the dynamic base model as in equation (4.2) through the fixed effect approach, column C presents the estimation result of the dynamic base model as in equation (4.2) through two-step system generalised method of moments approach, column D is the estimation result of the dynamic base model as in equation (4.2) through two-step system generalised method of moments approach by adding the quadratic term of $SIZE_{it}$, column E displays the estimation result of the dynamic extended model when adding on the dummy variable $TBTF_i$ and its interaction term with $T1_{it}$ (as in equation 4.4) through two-step system generalised method of moments approach, column F shows the estimation result of the dynamic extended model when adding on another set of macroeconomic determinants of $CAPGDP_t$, $SHIBOR_t$, $ALIBOR_t$ and $AGDPGR_t$ (as in equation, 4.6) through two-step system generalised method of moments approach.

R-sq represents the R squared value (overall) to show the fitness of the OLS and FE estimation, Hansen J-statistic test the joint validity of all instrumental variables included, difference-in-Hansen test confirms the validity of specified subsets instruments, AR (1) and AR (2) are the Arellano-Bond test for checking the assumption of no autocorrelation in error terms.

4.5.4 Determinants of Bank Stability

4.5.4a The Baseline Model

This section presents the analysis of empirical results generated by the baseline stability specification (equation 4.3). The examination of post-estimation tests is provided first, then is the model findings are explored. The parameter estimates from equation (4.3) are displayed in Table 4.15, below. Similar to our interpretation of model results from equation (3.23) in section 3.6 and equation (4.2) in section 4.5.3, the empirical results from the ordinary least squares and fixed effects estimation in equation (4.3) are also offered in this table, for comparison[175]. As expected, Table 4.15 shows that the lagged dependent variable $\ln(Z_{it-1})$ has highly significant effects on bank stability with all three modelling techniques; the coefficient for $\ln(Z_{it-1})$ produced utilising system GMM (0.479; see column C) is higher than the FE estimate (0.408, see column B) and lower than the OLS estimate (0.544, see column A).

Furthermore, the baseline equation (4.3) meets all model conditions for system GMM estimation (see column C of Table 4.15). Specifically, the number of instruments used (61) is smaller than the number of groups (97) recognised in the estimation. The Hansen J-statistic (0.328) validates the exogeneity of the instruments used and implies the IVs are not correlated with model error terms. Similar considerations apply to the difference-in-Hansen test, with a value of 0.205 for the lagged term $\ln(Z_{it-1})$ and a value of 0.466 for the levels equation, which indicate that subsets of IVs used in the estimation are valid instruments. The Arellano-Bond test confirms no autocorrelation in model error terms, given AR (1) has a p value of 0.001 and AR (2) of 0.413. Hence, the baseline regression (4.3) offers efficient estimators of the true parameters and assists us with the interpretation of the determinants of financial stability of Chinese banks.

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[175] See the motivation for incorporating the ordinary least squares and fixed effect estimation in section 3.6 (page 175-176).

As shown in column C of Table 4.15, $\ln(Z_{it-1})$ is found to be a significant and positive determinant, validating the persistence of stability in the Chinese banking sector over the sample period. This indicates that bank stability should be considered in a dynamic sense: the robust performance of banks in the previous year increases current levels of stability. A parameter value of 0.479 suggests that stability persists at a moderate level – a value approaching 0 means a high speed of adjustment, whereas a value close to 1 means a low speed of adjustment (Athanasoglou, Brissimis and Delis, 2008).

This observed persistence of stability in the case of Chinese banks could be a reflection of government interventions. For instance, to ensure the soundness of its banking sector, the Chinese government requires a minimum of 150% for the provision coverage ratio (the ratio of provisioning to non-performing assets) from banks[176]. To comply with these regulations, our finding shows Chinese banks' intention to build on both their previous stability levels and their ability to increase their stability going forward.

CE_{it} generates a significant and negative coefficient (-0.044, see column C of Table 4.15), which indicates that bank stability declines as cost efficiency scores increase. Such an adverse influence could be explained by banks' cost skimping behaviours. The cost skimping hypothesis, proposed by Berger and DeYoung (1997), describes a practice where bank managers intentionally put less effort into credit monitoring in order to minimise short-run operating costs and realise long-run profits. Under this circumstance, banks can enjoy a temporary increase in cost efficiency as less resources are devoted to producing the same quantity of outputs. However, the inadequate monitoring of the quality of loans could give rise to increases in future non-performing loans (such a tendency is highlighted by the rise of non-performing loans during 2010-2015 in our case – see Figure 3.3). The resulting increases in credit risk hinder bank solvency. This finding emphasises the significance of prudential lending strategies for enhancing bank stability in China. Moreover, our result is in accordance with Altunbas

[176] Also, the China Banking Regulatory Commission has, since 2006, imposed a 5% cap on the non-performing loans to total loans ratio for Chinese commercial banks.

et al. (2007) and Zhang et al. (2013), whose studies find strong evidence in favour of the cost skimping hypothesis.

$SHADOW_{it}$ is found to be positively but not significantly related to bank stability, with a parameter value of 0.001 (see column C of Table 4.15). This suggests that the growth of shadow banking activities tended to improve the viability of the Chinese banking sector during the sample period. This stabilising effect may be partially attributed to the benefits of risk diversification. That is, a variety of shadow banking activities promote a more diversified asset structure and hence enables a bank to diversify away non-systemic risks due to the less than perfect correlations among different types of activities. Another possible explanation is that expansions in shadow banking activities stimulate banking competition within the Chinese financial system (Ding, Fung and Jia, 2015, Li and Lin, 2016 and Luo et al., 2019). The strengthened competition lowers interest rates on loans and thus lessens banks' moral hazard and reduces concerns about adverse selection (Boyd and Nicolo, 2005), thereby decreasing the probability of bankruptcy of Chinese banks.

Nevertheless, this favourable stabilising effect is exercised by sample banks only to a very limited extent, given that the obtained coefficient on $SHADOW_{it}$ is statistically non-significant. This might be because the favourable effect is countered by the risks embedded in shadow banking transactions. For instance, engaging in shadow banking activities reduces intra-industry diversification,[177] which in turn increases in systemic risk in the Chinese banking industry[178]. In addition, as was pointed out in section 4.2, most Chinese banks utilise shadow banking activities as a form of regulatory arbitrage, that is, to circumvent prudent capital regulations and liquidity constraints to allow themselves to take excessive risks in order to boost profit (Hou et

[177] This is because participating in shadow banking operations has made large Chinese banks become very similar, since managers are now better able to act as a 'herd' in utilising business models that are much like those of their opponents (Zhou and Wang, 2008).

[178] That is, systemic risk could increase when most of banks share similar trading positions in the shadow banking markets and issue credits with the same type of collateral (De Jonghe, 2010). Then, in the event of large-scale default, the liquidity and capital base of banks will be quickly drained and lead to their insolvency (Anginer, Demirgüç-Kunt and Mare, 2018).

al., 2018). Yet, the resulting opaque debt structure contributes to the greater fragility of Chinese banks[179].

Table 4.15 (column C) shows a positive but again non-significant coefficient (0.027) for $SFTF_{it}$, implying the utilisation of short-term wholesale funding tends to have a positive effect on bank stability. On the one hand, Huang and Ratnovski (2008) and Köhler (2015) propose that short-term wholesale funds reduce bank risks through capital diversification and the disciplining from financiers. This funding strategy also notably diversifies funding sources for sample banks and, later, the strengthened liquidity position of banks will improve their ability to withstand adverse shocks (Tran, Lin and Nguyen, 2016). On the other hand, compared with deposit funding, short-term wholesale funding is more risky and over-reliance on these funds could increase bank fragility (Khan, Scheule and Wu, 2017). To illustrate, in a stressed scenario, banks with a high portion of short-term wholesale funding are more prone to a potential liquidity crisis (or even bankruptcy) if there is a sudden end to access to wholesale funds in the market[180]. Our finding indicates that a stable funding structure needs to be devised by Chinese banks to allow them to enjoy the significant risk-reduction effects of $SFTF_{it}$ while efficiently managing its associated risks.

$T1_{it}$ has a significant and positive effect on bank stability, with a parameter value of 0.027 (see column C of Table 4.15). Evidently, banks with higher levels of T1 capital have greater viability in China. This result corresponds to the findings of a number of prior studies, including Berger and Bouwman (2010), Mirzaei, Moore and Liu (2013) and Anginera, Demirgüc-Kunt and Mare (2018). Generally, at the bank level, higher capital holding strengthens managers' ability to monitor risk and screen borrowers, as well as improving banks' loss absorption capacity and so ability to withstand portfolio

[179] The fact that banks can aggressively conduct such regulatory arbitrage suggests significant regulatory gaps in the Chinese banking system. These shadow banking operations that can spread systemic risk across markets will be the areas attracting increasing attention from central supervisory authorities in the future.

[180] During periods of financial stress, investors' liquidity hoarding behaviours (banks become more cautious and so prefer to hoard their liquidity surplus than lend) could freeze the wholesale capital markets.

risk. Consequently, better-capitalised banks tend to be more robust. Furthermore, the enhanced capital base at the bank level has broader benefits at the system level, owing to the reduced contagious defaults across banks. That is, holding more T1 capital can mitigate contagious defaults by providing a buffer to shield against unexpected financial and/or economic shocks and breaking the chain reaction caused by the failure of individual banks (Duran and Lozano-Vivas, 2015 and Varotto and Zhao, 2018). Indeed, the importance of additional capital buffers in reducing systemic risk to ensure the stability of the banking system and the broader economy is emphasised by tightened Basel III capital requirements. Our result advises that the implementation of the Basel III regime in China encourages banks to exploit higher levels of financial stability.

In terms of $NPLs_{it}$, Table 4.15 (column C) documents a non-significant positive coefficient (0.028), which indicates that variation in bank stability is not associated with variation in the balance of non-performing loans. As explained in section 2.5, the establishment of four asset management companies and banking recapitalisation reforms, together with the 'well above minimum regulatory requirement' capital holding (see Figure 2.12), have remarkably shifted the NPL burdens away from Chinese banks.

Whereas the significant and positive coefficient (0.129, see column C of Table 4.15) estimated for $SIZE_{it}$ indicates that larger banks are more stable than smaller banks, perhaps because they are less sensitive to adverse shocks than smaller banks. Larger size is associated with higher levels of earnings,[181] so these banks are less vulnerable if downside risks materialise. Moreover, large banks usually have better-diversified asset structures and associated risks could be reduced through diversification, resulting in more robust banking operations.

We move on now to discuss how the market and macroeconomic environment impacts

[181] Our baseline bank profitability specification (4.2) yields a significant and positive correlation between $SIZE_{it}$ and profits (see page 270 of section 4.5.3)

the solvency of Chinese banks. It seems that bank stability is less sensitive to the effects of exogenous macroeconomic settings (than to intra-bank settings), considering that only INF_t and ER_t are significantly correlated with $\ln(Z_{it})$ in our model (see column C of Table 4.15). The remaining determinants – PGR_t, $GDPGR_t$ and IR_t – are not significantly associated with the soundness of Chinese banks. With respect to INF_t, its negative coefficient (-0.129) indicates that higher rates of inflation weakened bank stability over the sample period. This could be because higher inflation reduces the income revenues of debt borrowers and hence impairs their debt-servicing capacity. The resultant poor quality of loan portfolios (with greater credit risk) increases the risk of bank insolvency. Similar explanations can be seen in Soedarmono, Machrouh and Tarazi (2011), Lee, Yang and Chang (2014) and Umar and Sun (2018).

ER_t, representing the foreign exchange rate, can dramatically jeopardise banks, given its large negative correlation (-0.863, see column C of Table 4.15) with $\ln(Z_{it})$. Fluctuations in exchange rate undermine bank stability through their impacts on the real economy. In general, a country's real economy can be affected by exchange rate variations through two channels, the financial channel and the regular trade channel. Firstly, the financial channel influences economic activities through the liability side of the balance sheet of domestic borrowers because of the valuation changes that take place with exchange rate variations (Eichler and Littke, 2018). These changes in balance sheets alter risk-taking behaviours. To illustrate, the depreciation of the domestic currency will reduce the asset quality of domestic borrowers and damage the nation's real economy. Therefore, we find Chinese banks become more vulnerable when the domestic currency (CNY) depreciates. Gounopoulos et al. (2013) and Bessler and Kurmann (2014) hold the view that the direct exchange rate risk is simple to identify and to hedge against, and that what banks need to be cautious about is the foreign exchange risk which arises from indirect sources or other types of market risk, such as the interest rate risk.

Secondly, the regular trade channel affects economic activities via net exports, and lower levels of exports will undermine the stability of domestic banks due to the reductions in bank income margins (Quagliariello, 2008). Our sample raises an interesting question – government decisions on the selection of the exchange rate system usually neglect its implications for bank stability. During the Asian Financial Crisis, banking systems were more severely threatened in those countries that operated a fixed exchange rate; our findings therefore could call for a fully floating exchange rate policy in China[182].

4.5.4b The Extended Models

As indicated earlier, two extended stability specifications (equations 4.5 and 4.7) are introduced as regressions. That is, to investigate the significance of 'too big to fail', the dummy variable $TBTF_i$ and its interaction term with $T1_{it}$ are added to the baseline regression (4.3) to give equation (4.5). Then, to perform a thorough examination of environmental effects on bank stability, another set of macroeconomic determinates – $CAPGDP_t$, $SHIBOR_t$, $ALIBOR_t$ and $AGDPGR_t$ – are added into the model specification, transforming the baseline equation (4.3) to equation (4.7). The model results of regressions (4.5) and (4.7) are presented in columns D and E of Table 4.15 below, respectively. Prior to any interpretations of our findings, the pre- and post-estimation tests are performed.

The instrument proliferation problem is absent, as the number of groups (97/97) identified in the sample dataset is larger than the number of instruments (81/59) utilised during the estimation for equation (4.3)/(4.7). The generated Hansen J-statistic (0.477/0.221) certifies the exogeneity of employed instruments by accepting the null hypothesis that instrumental variables are valid instruments and uncorrelated

[182] As argued by Fratianni, Salvatore and Savona (1998), "*whether fixed or flexible exchange rates are preferable depends on the source of disturbances. For example, when threats to the stability of the banking system take the form of fluctuations in world interest rates that make it more difficult for banks to fund themselves offshore, there will be a case for exchange rate flexibility to discourage the banks from relying excessively on external sources of finance and to enhance the capacity of the domestic authorities to act as lenders of last resort*" (page 199). In contrast, fixing the exchange rate will be a wise option if the primary disturbances originate from erratic monetary policy at the domestic level. The choice to peg the exchange rate works effectively, in this case, to discipline domestic policymakers and vent shocks via the external sector (Eichler and Littke, 2018). In the current banking scene, a semi-floating exchange rate scheme seems to be efficient. A call for a fully market-based exchange rate regime seems imminent for China, given the increasing international presence within the Chinese banking system.

with error terms. The difference-in-Hansen test yields a test statistic of 0.667/0.350 for $ln(Z_{it-1})$ and 0.619/0.680 for the levels equation, supporting the validity of subsets of instruments adopted in models. No serial correlation problems are detected, as the p value for AR (1) is 0.002/0.002 and 0.371/0.355 for AR (2). Thus, the post-estimation diagnostics are satisfied, and so the parameter estimates provide a valid basis for our financial stability reviews of the Chinese banking system.

Table 4.15 (column D) reports a significant positive coefficient (1.349) for the dummy variable $TBTF_i$. In light of the policy debate over 'too big to fail', our model finds that Chinese TBTF banks operated more robustly than non-TBTF banks during the observation period. The need for large financial institutions to be reduced in size seems not to be supported by our Chinese sample. Concerning the main effects of $T1_{it}$, a parameter estimate of 0.040 is obtained, indicating that higher values of $T1_{it}$ lower the probability of bankruptcy for Chinese non-TBTF banks (the TBTF dummy variable taking the value of 0). As for Chinese TBTF banks (the dummy variable taking the value of 1), the sum of parameter values of $T1_{it}$ (0.040) and the interaction term $T1_{it} * TBTF_i$ (-0.190) represents the impacts of $T1_{it}$ on bank stability for these banks. The corresponding value of -0.150 (statistically significant at the 5% level) suggests that the viability of Chinese TBTF banks will be reduced if these banks increase their T1 capital holding[183].

Over the sample period, complying with the tighter capital regulations, Chinese TBTF banks built additional capital buffers to increase their loss absorbency capacity in order to be able to continue supporting the Chinese economy throughout the credit cycle. As a result, during this period, Chinese TBTF banks held much higher levels of T1 capital than the minimum requirement stipulated by the Basel criteria. More specifically, from 2005 to 2015, the respective annual average levels of T1 capital holding of Chinese TBTF banks were 6.63%, 7.36%, 8.49%, 8.62%, 8.04%, 9.20%, 9.55%, 9.74%, 9.12%,

[183] This finding is similar to what was found in an earlier global financial stability study conducted by IMF (2009). The report draws on a dataset of 36 leading international banks, and finds that banks without the need of government interventions carried statistically lower levels of equity capital prior to the GFC, compared with banks that were helped during the crisis.

9.77%, and 10.41%, whereas the Basel criteria require a minimum level of only 6%. Our result demonstrates that at high capitalisation levels, further increases in capital actually introduce moral hazard incentives amongst Chinese TBTF banks[184] as the probability of insolvency is extremely low. Moreover, Zhang et al. (2016) argue that the protection offered by the deposit insurance scheme[185] further encourages Chinese TBTF banks to take undue risks that maximise their subsidies while passing losses to the government.

Table 4.15 (column E) reports that coefficient on $CAPGDP_t$ is statistically non-significant, indicating that the development of the Chinese equity market does not seem to affect the stability of the Chinese banking market. With respect to $SHIBOR_t$, increases in the interbank offered rate erode bank soundness, as shown by the significant negative coefficient (-0.253, see column E of Table 4.15). On the one hand, the interbank offered rate generally fluctuates within its normal range but an increase in this rate can substantially increase the liquidity and capital costs of Chinese banks. On the other hand, in extreme adverse cases, an abnormal surge in the interbank offered rate normally leads to serious disruptions in (or even a breakdown of) the interbank market, which exposes banks to liquidity shortage and wipes out banks' capital base when subsequent defaults kick in (Affinito and Franco Pozzolo, 2017).

Indeed, during the crisis period, Heider, Hoerova and Holthausen (2015) point out that "*only an adverse selection of riskier banks keeps borrowing unsecured, causing the interest rate to increase. When the higher average counterparty risk is combined with high dispersion, liquidity hoarding ensues, lenders prefer to keep liquidity instead of lending it out despite the high rates borrowers would be willing to pay*" (page 35). Drawing on experiences of the GFC, such liquidity hoarding behaviours froze the

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[184] To recap, moral hazard incentives could arise when bank managers know that their institutions have TBTF status and able to accept undue risks because a government bailout will occur if needed (Altunbas, Binici and Gambacorta, 2018).

[185] China proposed a deposit insurance scheme in 2015, endeavouring to free up the domestic interest rate and advocate market-based capital allocation. This scheme, as its name suggests, provides an explicit deposit protection between banks and government to settle the risk of bank runs (Boyle et al., 2015).

interbank market, causing the bankruptcy of numerous banking institutions across the world and eventually leading to a system-wide financial crisis in 2008. Thus, our model suggests that Chinese banks call for more close monitoring because of their critical performance in the funding market to ensure the solvency of their business.

Both $ALIBOR_t$ and $AGDPGR_t$ show a non-significant correlation with $\ln(Z_{it})$ (see column E of Table 4.15). This may indicate that the sources of disturbance that threaten the safety of the Chinese banking industry basically take the form of fluctuations in domestic economic conditions. Bhimjee, Ramos and Dias (2016) suggest that risk contagion is most likely when a majority of banks are exposed to a common counterparty. However, the size of such risky exposures is rather limited in Chinese banks. Moreover, Bai et al. (2019) point out that the stability of the Chinese banking system is less driven by the global financial cycle because of China's heavy government interventions.

Table 4.15: Empirical findings for proposed bank stability specifications.

Variables	OLS – equation (4.3)	FE – equation (4.3)	GMM – equation (4.3)	GMM – equation (4.5)	GMM – equation (4.7)
	A	B	C	D	E
$\ln(Z_{it-1})$	0.544***	0.408***	0.479***	0.493***	0.557***
	(0.034)	(0.044)	(0.074)	(0.092)	(0.113)
CE_{it}	0.002	0.007	-0.044**	-0.029**	0.037*
	(0.014)	(0.016)	(0.018)	(0.014)	(0.020)
$SHADOW_{it}$	0.000	0.000	0.001	0.004	-0.003
	(0.002)	(0.003)	(0.004)	(0.004)	(0.002)
$SFTF_{it}$	-0.002	-0.001	0.027	-0.011	-0.007
	(0.006)	(0.009)	(0.023)	(0.019)	(0.007)
$T1_{it}$	0.022***	0.036**	0.027**	0.040***	0.021**
	(0.008)	(0.014)	(0.011)	(0.012)	(0.008)
$NPLs_{it}$	-0.002	0.009	0.028	0.023	0.003
	(0.013)	(0.016)	(0.030)	(0.017)	(0.013)
$SIZE_{it}$	0.080***	0.099	0.129***	0.266**	0.079***
	(0.020)	(0.186)	(0.044)	(0.118)	(0.026)
PGR_t	0.006*	0.002	-0.001	-0.002	-0.018*
	(0.003)	(0.004)	(0.004)	(0.004)	(0.010)
$GDPGR_t$	0.139**	0.121*	0.077	0.036	-0.160
	(0.065)	(0.067)	(0.076)	(0.072)	(0.224)
INF_t	0.062	0.031	-0.129*	-0.067	-0.015
	(0.070)	(0.075)	(0.075)	(0.066)	(0.060)
IR_t	0.061	0.063	-0.035	-0.003	-1.350
	(0.043)	(0.045)	(0.048)	(0.042)	(1.487)
ER_t	-1.135***	-1.028***	-0.863**	-0.538	0.557
	(0.317)	(0.347)	(0.449)	(0.442)	(0.013)

$\_cons$	6.255***	5.451	9.625***	4.392	7.369
	(1.698)	(3.404)	(2.909)	(3.770)	(9.335)
$TBTF_i$				1.349*	
				(0.707)	
$T1_{it} * TBTF_i$				-0.190***	
				(0.063)	
$CAPGDP_t$					0.016
					(0.013)
$SHIBOR_t$					-0.253*
					(0.151)
$ALIBOR_t$					0.293
					(0.327)
$AGDPGR_t$					-0.564
					(0.300)
R-sq (overall)	0.488	0.480			
Breusch-Pagan	0.001				
Modified Wald test		0.000			
Number of IVs (groups)			61(97)	81(97)	59(97)
Hansen-J-statistics			0.328	0.477	0.221
Difference-in-Hansen test ($\ln(Z_{it-1})$)			0.205	0.667	0.350
Difference-in-Hansen test for levels equation			0.466	0.619	0.680
AR (1)			0.001	0.002	0.002
AR (2)			0.413	0.371	0.355

**Correlation is statistically significantly different from zero at the 10% level, **Correlation is statistically significantly different from zero at the 5% level, ***Correlation is statistically significantly different from zero at the 1% level. Standard errors are in parenthesis.*

$ln(Z_{it-1})$: the autoregressive term, CE_{it}: cost efficiency scores (%), $SHADOW_{it}$: bank shadow exposures to total assets ratio (%), $SFTF_{it}$: short-term funding to total funding ratio (%), $T1_{it}$: Tier 1 regulatory capital ratio (%), $NPLs_{it}$: non-performing loans ratio (%), $SIZE_{it}$: natural logarithm of bank size, PGR_t: annual growth rate of industrial profits (%), $GDPGR_t$: national annual GDP growth rate (%), INF_t: national annual inflation rate (%), IR_t: national annual real interest rate (%), ER_t: national annual exchange rate against US dollar (%), $TBTF_i$: a dummy variable that takes a value of 1 for domestic systemically important banks and 0 for the

remaining banks, $T1_{it} * TBTF_i$: the interaction term of $T1_{it}$ and $TBTF_i$, $CAPGDP_t$: market capitalisation to GDP ratio (%), $SHIBOR_t$: 3-month Shanghai interbank offered rate (%), $ALIBOR_t$: aggregated interbank offered rate of the US, UK, Europe, Japan and Hong Kong (%), and $AGDPGR_t$: aggregated national annual GDP growth rate of the US, UK, Europe, Japan and Hong Kong (%).

Column A shows the estimation result of the dynamic base model as in equation (4.3) through the ordinary least squares approach, column B is the estimation result of the dynamic base model as in equation (4.3) through the fixed effects approach, column C presents the estimation result of the dynamic base model as in equation (4.3) through the two-step system generalised method of moments approach, column D displays the estimation result of the dynamic extended model when adding the dummy variable $TBTF_i$ and its interaction term with $T1_{it}$ (as in equation 4.5) through the two-step system generalised method of moments approach, column E shows the estimation result of the dynamic extended model when adding another set of macroeconomic determinants, namely $CAPGDP_t$, $SHIBOR_t$, $ALIBOR_t$ and $AGDPGR_t$ (as in equation 4.7) through the two-step system generalised method of moments approach.

R-sq represents the R squared value (overall) to show the fitness of the OLS and FE estimations, Hansen J-statistics test the joint validity of all instrumental variables included, difference-in-Hansen test confirms the validity of specified subsets instruments, AR (1) and AR (2) are the Arellano-Bond test for checking the assumption of no autocorrelation in error terms.

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4.6 Conclusion

Against a background of ongoing banking reforms in China, it seems premature to reach conclusions regarding the impacts of these transformations on the performance of the Chinese banking system. Yet, its success is crucial for China's real economy and it is of interest to examine the changes from both domestic and global perspectives. Accordingly, this chapter evaluates the cost of recapitalisation, cost efficiency, profitability and stability performance of Chinese banks over the period 2005 to 2015, with the utilisation of an unbalanced panel dataset. Overall, our analysis contributes to current banking literature with a more comprehensive framework to study Chinese banks. This chapter first estimates shadow return on equity on the basis of a stochastic frontier cost function to analyse the effects of recapitalisation on Chinese banks. The results reveal that, initially, Chinese banks exhibited a highly leveraged debt financing and equity capital was underused in relation to what might be considered prudent. The recapitalisation then decreased the funding costs in the Chinese banking market and banks adjusted their position from a highly leveraged equilibrium one to one with lower leverage over the period 2005 to 2015, a pattern consistent with increasing utilisation of equity capital.

We then derive cost efficiency scores for sample banks through the stochastic frontier analysis. This modelling technique is employed because it distinguishes between the inefficiency effects and the random error term and allows the direct inclusion of exogenous variables in the cost specification. Overall, Chinese banks experienced cost efficiency gains prior to the GFC but saw deteriorations thereafter. Accordingly, our study finds strong evidence in favour of the bad luck and bad management hypotheses in the context of Chinese banking. Among the determinants of cost inefficiency, those connected with the macroeconomic environment, namely stronger economic growth, lower inflation and the exchange rate can benefit the cost performance of Chinese banks. In particular, the variation in cost efficiency is found to be highly sensitive to the variation in exchange rate during the sample period.

Next, our study conducts the profitability determinants analysis for Chinese banks through system GMM regressions and the proposed models yield several interesting findings. Specifically, profitability has the feature of persistence in the Chinese banking industry. This potentially signals impediments to competition (e.g., government interventions) within the domestic banking market. Higher levels of profitability were experienced by banks with greater cost efficiency scores and larger proportions of short-term wholesale funding. In addition, aggressive expansion of their shadow banking activities by Chinese banks reflects their wish to diversify their profit composition in favour of revenues generated from risky market-based investments. In these circumstances, we find that Chinese banks need to enhance their capacity to manage the implicit costs related to shadow banking transactions in order to realise significant increases in profits. The size variable has positive impacts on bank profitability, yet this positive correlation holds only for large sample banks whose size is above CNY587,029.29 million[186]. Accordingly, regulations that limit the size of large financial institutions would bring economic costs for Chinese large banks in the form of forgone profits.

Across the observation period, tightened Basel III capital requirements positively affected the profitability of Chinese TBTF banks, while fulfilling the newly implemented capital rules contributed to profit vulnerabilities of non-TBTF banks. It seems that complying with more strict prudential rules put non-TBTF banks at a competitive disadvantage. In addition, the development of the Chinese equity market has hindered bank profits, possibly because the enhancements of the equity market largely diversify capital sources for Chinese enterprises and investors, and hence reduce the market demand for bank credit. In our case, Chinese banks' earning ability is shown to be considerably driven by the domestic macroeconomic settings. That is, stronger economic growth, lower inflation and the interbank offered rate appear to strengthen profitability, whereas depreciation of the exchange rate decreases it. Meanwhile, our findings confirm that financial contagion effects could arise from the international interbank market whereby a higher aggregated interbank rate increases the profits of

[186] When sample banks' asset size is below this threshold, increases in size reduce bank profitability.

domestic banks.

Finally, the determinants of the stability of Chinese banks are investigated in this chapter. The results indicate that stability persists to a moderate level in the Chinese banking sector. Better-capitalised banks are observed to be more robust than thinly capitalised banks, and the same is true for Chinese banks with larger asset size. In contrast, lower levels of stability are found for Chinese banks with higher cost efficiency scores, a conclusion in favour of the cost skimping hypothesis. Moreover, we notice that, to a very limited extent, Chinese banks are seeing risk-reduction gains from the growth of their shadow banking activities through asset diversification and from the utilisation of short-term wholesale funding through capital diversification. Nevertheless, such gains can be easily offset by the high risks embedded in these transactions.

Interestingly, in the case of our sample, TBTF banks seem to be more robust operations than non-TBTF banks. Therefore, again, our results do not confirm the need to downsize large banks in China. The tightened Basel III capital rules efficiently enhance the solvency of non-TBTF banks, while sufficient T1 capital holding leads to an increase in moral hazard among TBTF banks. This reminds Chinese policy makers to be cautious about the fact that, although increases in equity capital could help banks to absorb financial losses and thereby strengthen stability, overcapitalisation could be an indicator of managerial inefficiency and incentivises overcapitalised banks to take undue risks. Among the macroeconomic determinants considered, exogenous threats to the resilience of Chinese banks primarily take the form of fluctuations in the exchange rate and the interbank offered rate. Such findings offer a rationale calling for a fully floating exchange rate regime in China.

Chapter 5

Conclusion and Limitations

5.1 Conclusion

Focusing on the Chinese banking system over the period 2005 to 2015, the objective of this thesis is four-layered. First, considering the policy debate on 'too big to fail', we link the investigation of scale economies with scale efficiency to analyse size benefits and/or costs in the Chinese banking sector. Second, the cost efficiency performance of Chinese banks is focused upon. The stochastic frontier analysis (SFA) technique is utilised to estimate individual cost efficiency scores for banks, and to enable the direct incorporation of exogenous factors in the cost function to examine the determinants of the inefficiency effects. Third, in view of the ongoing financial reforms in China, we extend the previous banking literature on profitability determinants analysis to identify the driving factors that account for the low profitability of Chinese banks over the sample period. Finally, the variables that underly the resilience of Chinese banks are evaluated with the aim of maintaining the stability of the Chinese banking system.

Our analysis starts with Chapter 2 – an overview of the Chinese banking industry. In short, the history, structure, regulatory reforms, recent performance, as well as current restructuring of balance sheets of the Chinese banking sector are discussed in that chapter. We first present a brief historical review of Chinese banks for the years 1978 to 2015. Over this period, due to financial liberalisation and deregulation, the Chinese banking system witnessed a series of unprecedented structural and institutional reforms, such as the establishment of banks with different types of ownership, the foundation of the interbank market, the permission of foreign bank operation, and the implementation of the Basel regimes (see Table 2.1 for a summary of major banking reforms in China across this period). In general, these transformations remarkably improved the competitiveness and international presence of Chinese banks.

Moreover, thanks to these reforms, the Chinese banking system evolved from a 'single institution' (only one bank in the financial system) to the modern 'multi-tiered structure' with banks with different ownership structures and asset scales.

In addition, China has enforced a set of initiatives to ease the legacy non-performing loans and strengthen the capital position of banks (as discussed in sections 2.5 and 2.6). With the disposal of non-performing loans and the beginning of recapitalisation, prior to the start of the GFC, Chinese banks had experienced a period of efficiency and profitability gains following an upward economic cycle. Then the financial crisis hit Chinese banks, imposing great pressures on their earnings (e.g., the industry average of banks' return on equity ratio declined from 16% in 2008 to 13% in 2017). Besides, various balance sheet restructurings have been undertaken by Chinese banks in order to adapt to their new operating environment. Two such underlying changes are the shifting of bank assets towards shadow banking activities and the increasing reliance of banks on short-term wholesale funds. The involvement of Chinese banks in shadow banking activities and the utilisation of short-term wholesale funding could generate profit gains but with excessive risk taking. Indeed, these banking activities could give rise to substantial increases in financial risks on both the asset and the liability sides and encourage systemic risk to build within the banking market, drawing regulators' concern.

In light of the policy debate over too big to fail (TBTF), Chapter 3 analyses the scale economies, scale efficiency and technological change of Chinese banks to inspect whether industry consolidation is a rational aim for larger banks in China to continue grow in asset scale. To obtain scale economies and efficiency estimates, a comprehensive translog cost function that captures risks in the bank production process by including risk control variables in the cost specification is estimated. Importantly, unlike previous banking studies that also considering managers' risk preference in constructing a cost function, our study incorporates three risk factors separately and in different combinations. We then employ the Li test proposed by Li (1996, 1999) to identify which risk variable should be considered when considering the best fitted cost specification regarding the scale estimation of the Chinese banking system. Based on the results of the Li test, our study finds that all three specified risk factors should be included in the cost function.

Our cost function finds evidence of minor diseconomies of scale for the whole sample over the observation period, yet significant economies of scale are observed for large Chinese banks, i.e., those allocated to asset quartile 4 (the quartile with the highest asset value when dividing the full sample into four quartiles according to asset size). In addition, estimating the cost function parameterised for Chinese non-TBTF banks, we confirm that such cost savings practised by these biggest banks in our sample indeed indicate scale economies rather than TBTF subsidies. Therefore, recent regulatory recommendations that imply a downsizing of large financial institutions would induce economic costs for large Chinese banks in the form of forgone scale economies. Our results also suggest that neglecting the costs of financial risks could result in biased scale efficiency estimates for Chinese banks – the inclusion of risk variables in the cost function notably decreases the levels of scale efficiency for banks.

When splitting the full sample via clustering analysis and analysing banks in more accurate groupings in terms of portfolio composition, our research is the first empirical study (to the best of our knowledge) to demonstrate that size alone is an inadequate categorising criterion for Chinese banks. We note that substantial economies of scale are exploited by banks in cluster 1 and cluster 4 (mainly large Chinese state-owned commercial banks) through expansion of off-balance sheet operations. On average, banks in cluster 2 present constant returns to scale, implying that medium-large and large Chinese joint-stock banks with a high proportion of short-term funding are operating at the optimum scale based on their product mix. The obtained estimates of technological change justify bank consolidation and indicate that technological progress has increased the comparative advantages of large-scale operations in the Chinese banking system. The final section of Chapter 3 focuses on an evaluation of the determinants of economies of scale of Chinese banks with the help of generalised method of moments (GMM) regressions. The findings show that banks with higher liquidity, lower credit risk and the TBTF status can realise more cost economies.

In the context of ongoing banking transformations in China, Chapter 4 assesses the cost of recapitalisation, cost efficiency, profitability and stability performance of the Chinese banking sector. Following Battese and Coelli (1995), Chapter 4 proposes a stochastic frontier cost specification to estimate the shadow return on equity and cost efficiency scores for Chinese banks. The focus is on the evaluation of shadow return on equity and on an analysis of the effects of recapitalisation on Chinese banks. The results reveal that recapitalisation indeed reduces funding costs for banks. Meanwhile, Chinese banks are adjusting from one highly leveraged equilibrium position to another with lower leverage – a pattern consistent with the increasing utilisation of equity capital by banks.

With respect to the cost efficiency estimation, our frontier cost specification assumes the minimisation of bank cost is contingent on five factors: managerial inefficiency, risk considerations, environmental effects, time trend and statistical noise. The efficiency scores are then derived based on the cost function through the SFA modelling approach. Reviewing the evolution of efficiency scores over the sample period, 2005-2015, we identify that Chinese banks realised greater cost efficiency prior to the GFC; thereafter, cost efficiency exhibited an overall decreasing tendency. From the analysis of the inefficiency effects, it is evident that stronger economic growth, lower inflation and exchange rate appreciation boost the efficiency levels of Chinese banks. In addition, among sample banks, joint-stock and foreign banks are found to define the cost frontier, whereas state-owned banks illustrate the worst performance.

Drawing on the analysis of the profitability and stability determinants (via GMM models) of Chinese banks, our estimation yields several interesting findings that may inform bank managers and policy makers. Specifically, both profitability and stability display the feature of persistence in the Chinese banking system, potentially reflecting impediments to competition within the banking market. Instead of commonly utilised cost-related financial ratios (e.g., cost to income ratio) in most prior studies on bank profitability and stability, our study takes a step further, constructing stochastic frontier cost efficiency scores to examine the impacts of operating efficiency on bank performance in China. The empirical results suggest that deteriorations in cost efficiency contribute to the low profitability of Chinese banks. Hence, in order to enhance profitability, Chinese banks need to acquire superior risk management skills to realise higher levels of cost efficiency. However, the greater cost efficiency appears to hinder the stability of Chinese banks via cost skimping behaviours – a conclusion emphasising the need for prudent lending strategies to ensure bank solvency in China.

Contributing to the Chinese banking literature, to the best of our knowledge, this thesis is the first to explicitly investigate the influence of shadow banking activities on the profitability and stability of Chinese banks. In theory, as a form of regulatory arbitrage, the growth of shadow banking operations may lead to increases in bank profits through assets diversification, reduced regulatory burdens and technical innovations (Elsas, Hackethal and Holzhäuser, 2010 and Hou et al., 2018). Nevertheless, these profit gains come with costs, such as agency issues and managers' reckless rent-seeking attitudes. Empirically speaking, our estimation yields a non-significant negative correlation between shadow banking activities and bank profitability. This suggests that Chinese banks need to strengthen their ability to manage the associated implicit costs in order to exploit the profit-increasing effects of shadow banking operations. Our estimation also shows that the growth of shadow banking activities improves the solvency of Chinese banks through risk diversification, although such stabilising effects could be easily offset by the high risks (e.g., leverage risk and systemic risk) that come with shadow banking transactions. This indicates that for banks to fully realise the stabilising effects, managers need to ensure they have adequate risk monitoring of their shadow banking activities.

Our model finds that the utilisation of short-term wholesale funding facilitates the profit gains of Chinese banks and enables them to become more stable. However, one concern that needs to be raised is that over-reliance on these funds could cause banks to be more prone to liquidity problems if there is a sudden end to ready access to wholesale funds in the market. Besides, the policy recommendation of a size cap on large financial institutions is not supported by our Chinese sample, given larger banks are found to be more profitable and more stable than smaller banks in our estimation. Further, the positive correlation obtained with regard to asset scale and bank stability justifies the Chinese government's use of a merger and acquisition strategy as one of the primary means to stabilise the Chinese banking sector after the GFC. Moreover, our model concludes that the tougher Basel III capital requirements increase the profits of TBTF banks in China, but weaken the earning ability of non-TBTF banks. In terms of bank stability, the tightened Basel III capital rules have had positive effects on non-TBTF banks, whereas increasing the level of Tier 1 capital only increases TBTF banks' moral hazard issues.

When attention is directed to the influences of the macroeconomic environment, a macroeconomic setting that features stronger economic growth, reduced inflation and lower interbank offered rate is shown to boost profits in the Chinese banking sector. Conversely, the development of the equity market and exchange rate depreciation appear to reduce bank profits. Unlike profitability, the resilience of Chinese banks is less driven by the macroeconomic settings; exogenous threats that weaken the solvency of Chinese banks mainly take the form of fluctuations in the exchange rate and interbank offered rate.

5.2 Policy Implications

The empirical findings discussed above have various policy implications to Chinese bank managers, regulators and governmental authorities. First, scale economies that arise from off-balance sheet businesses suggest that diversification and deregulation do indeed contribute to the development of Chinese banking and should be considered in the policy agenda for the subsequent marketisation reforms of Chinese banks. The cost savings enjoyed by those largest banks in our sample suggest that policy initiatives that limit the size of large banks to alleviate TBTF concerns would put Chinese large banks at competitive disadvantage. Additionally, size restrictions may be ineffective as they work against market forces and induce banks to circumvent them. Evading the restrictions could therefore push risk-taking outside of the more regulated banking sector without necessarily decreasing systemic risk. In this sense, instead of downsizing, there is a need for Chinese regulatory authorities to introduce a series of new capital and liquidity requirements to update previous relaxed domestic regulations compliant with recent prudent international standards, in order to mitigate TBTF subsidies. Besides, the technological progress that has been shaping the Chinese market justifies bank consolidation and concentration. Hence, the industry-wide consolidation of efficient larger banks with inefficient smaller banks should be encouraged in the Chinese market for the aim of pursuing system efficiency.

Second, by examining the effects of recent regulatory reforms (in accordance with Basel III rules) on bank performance (i.e., scale economies, profitability and stability in our case), our findings suggest that policy makers should balance the need for soundness of the financial system with the need to encourage financial innovation and dynamism when they devise regulations for banking. That is, new banking regulations such as the Basel III regime impose constraints on banks in the form of more liquidity and capital and also to restrain riskier areas of banking operation – all of which are aiming at reducing systemic risk and strengthening banks' ability to withstand adverse shocks. However, satisfying such prudential rules could enforce significant costs on banks. In our sample, these costs refer to the reduced bank scale economies and profits. Thus, when formulating regulations for banks, policy markets should bear in mind the trade-off between safety of the industry and the cost of implementing these regulations. Moreover, when splitting the sample by the TBTF status for a comparative analysis, our estimation results question the Basel Committee's approach whereby it provides only a one-size-fits-all regulatory regime for a banking landscape with a wide expanse of smaller and regional banks, numerous medium-sized banks, as well as very large and complicated banks. Indeed, we suggest that various regulatory criteria should be formulated to fit different sizes of banks, in order to lessen the operational burdens imposed by the need to comply with complicated rules for non-TBTF banks.

Third, our findings with regard to cost efficiency estimation suggest that for banks to achieve greater cost efficiency, bank managers need to ensure they have superior risk management expertise. In addition, on the macroeconomic effects to bank cost efficiency, bank managers should be capable of responding to uncertainties related with changing macroeconomic settings such as inflation and GDP growth, among others.

This indicate that relevant monetary and fiscal policies aimed at stabilising inflation and sustaining the high GDP growth rate should be proposed by the Chinese government to boost bank efficiency.

Fourth, based on the empirical results of our bank profitability and financial stability determinants analysis, the following recommendations are made. (i) Chinese banks should improve their ability to manage the associated implicit costs in order to attain the profit-increasing effects of shadow banking activities. Banks also need to ensure they have adequate risk monitoring of their shadow banking operations to fully exploit the stabilising effects of shadow banking activities. Furthermore, the fact that banks can aggressively conduct such regulatory arbitrage practices suggests regulatory gaps in the Chinese banking system. This could be a call for the close monitoring of banks' market conduct to support timely and informed policy decisions regarding proper changes in regulations. (ii) Improper government interventions are found to impose costs on Chinese banks in terms of reduced profitability. This would suggest that Chinese government should consider carefully when conducting interventions in the banking sector, government interventions are supposed to be carried out in a sense of promoting a more competitive and stable domestic banking market, instead of inducing extra operational costs for banks. (iii) At country level, there is a justification for the employing of a semi-floating exchange rate scheme by the government in China to foster bank performance.

5.3 Limitations and Further Research Directions

This thesis offers evidence in regard to scale economies, cost efficiency, and the profit and stability performance of Chinese banks. Our findings, however, are nonetheless subject to limitations. For instance, the method used to examine whether estimated scale economies are affected by TBTF considerations will reveal the true parameters of the cost specification only if our approach to the identification of TBTF banks is appropriate. Although the approach employed seems to perform well, it is unlikely to be perfect. Besides, as discussed in section 3.4.2, the system GMM estimator adopted to conduct bank profitability and stability determinants analysis could suffer from the finite sample bias when weak instruments problem exists. In our study, this issue is addressed by allowing both lagged differences and lagged levels to be utilised as instruments during estimation. Recently, Jung et al. (2015) propose an alternative approach. That is, they suggest using a suboptimal weight matrix which contains the estimated variance ratio of the individual effects to that of the idiosyncratic error term for the system GMM estimator to reduce the finite sample bias whilst increasing its asymptotic efficiency. Although the method we used seems to behave well, future studies would be worthwhile to apply the aforementioned alternative approach to handle the finite sample bias for the purpose of enhancing the performance of the dynamic panel data model.

In addition, we choose the stochastic frontier approach (SFA) rather than data envelopment analysis (DEA) to estimate the cost efficiency of Chinese banks for the purpose of the thesis. More specifically, our proposed bank cost specification follows Batesse and Coelli (1995) in allowing the inefficiency term to be an explicit function of several exogenous (macroeconomic) factors and in assuming all bank-specific effects are components of the bank inefficiency term. Nevertheless, related empirical banking efficiency studies do not provide a consensus on whether or not these bank-specific time-invariant effects should be regarded as a part of this one-sided error term; it seems to be more of a choice depending on the explanation of empirical results (Kumbhakar, Lien and Hardaker, 2014). Consequently, for the future, it will be important to examine the efficiency of the Chinese banking by permitting the further decomposition of inefficiency in terms of bank-specific effects in a SFA model.

Moreover, our proposed stochastic cost function (4.13) assumes the minimisation of bank costs is contingent on five aspects, i.e., managerial inefficiency, time trend, risk effects, environmental effects and statistical noise. The board-related characteristics, such as board size, board independence and executive compensation, are not included in our cost specification for the purpose of the thesis – this could be a limitation of this thesis. Although a bank’s senior management and board of directors are primarily accountable and responsible for the performance of the bank, as highlighted by the

Basel Committee on Banking Supervision, the literature on bank cost efficiency dealing with the potential impacts of board-level governance is rather limited. Agoraki, Delis and Staikouras (2010) examine the association between board structure, in terms of board composition and size, and bank cost efficiency using a sample of European banks. They find an increased number of non-executive directors reduces cost efficiency and banks with smaller board size are more cost-efficient. Similarly, a negative correlation with regard to board size and bank cost efficiency is also documented in Ladipo and Nestor (2009), Adams and Mehran (2012) and Pathan and Faff (2013). These studies normally hold the view that the larger the board, the less effective it is at monitoring management. This could be due to greater agency costs, especially in terms of communication and coordination difficulties and free-riding issues among directors.

Employing a dataset of US commercial banks, Titova (2016) reports an inverted U-shape correlation between board size and bank cost efficiency, suggesting there is a trade-off between benefits and costs of larger boards. Besides, this paper finds an inverted U-shape association between board independence and efficiency. Specifically, lower levels of cost efficiency are observed for banks where the Chairman also executes the CEO responsibility. Nevertheless, a higher proportion of independent board members in banks with unitary leadership structure might mitigate the conflict of interest and lower efficiency stemming from CEO duality. Pathan, Skully and Wickramanayake (2007) present strong evidence to demonstrate the benefits of having independent directors. By examining Thai banks, the study finds that bank efficiency is enhanced by strengthening internal corporate governance mechanisms through greater board independence.[187]

Focusing on the evaluation of the impacts of executive compensation on efficiency of Chinese banks, Molyneux and Linh (2014) show that executive compensation adversely affects cost efficiency, which is attributed to managers abusing their power to design

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[187] Pathan, Skully and Wickramanayake (2007) demonstrate that independent directors tend to be more effective in decreasing opportunistic costs, disciplining and monitoring managers, and protecting the benefits of stakeholders, since they need to protect their reputation for independent directorships in the banking industry.

compensation packages that maximise their own benefits at the cost of banks. Such a negative influence is observed to be more severe during the GFC. In contrast, the empirical results yielded by Livne, Markarian and Mironov (2013) and Dong, Girardone and Kuo (2017) support the proposal that high executive compensation contributes to the greater efficiency of banks. They argue that the compensation scheme mitigates agency issues and impels top executives to improve their mutual monitoring activities. In this circumstance, more cost savings can be generated through strengthened internal corporate governance. Moreover, another key finding of Dong, Girardone and Kuo (2017) is that the greater gender diversity on boards (more female directors) introduce a positive effect on bank efficiency whilst reducing risk profile of banks. Such findings differ from several previous studies including Carter et al. (2010) and Pathan and Faff (2013), which reported the irrelevance of gender diversity for bank performance.

Overall, the empirical studies have obtained mixed results on the correlation between board-related characteristics and cost efficiency. As stated, only a small set of studies has reviewed the impacts of board-level variables on bank cost efficiency. For Chinese banking, the related empirical studies are even rare. One possible explanation for this phenomenon is that the data collection process for board governance research on the Chinese banking sector is challenging and time-consuming (Molyneux and Linh, 2014). Similarly, the reason for us not to consider board-related features in our cost efficiency estimation and second stage regressions is because our sample size limits our ability to fully collect corporate governance data for sample Chinese banks. That is, specifically, our study first attempts to collect corporate governance data for sample Chinese banks from two well-known databases in the banking literature – the Orbis Bank Focus Database and the SNL financial Platform. These two international databases contain high-quality financial data on Chinese banks. However, with respect to the corporate governance data, such as the variable of the total number of directors on the board, the variable of the number of independent directors on the board and the variable of executive compensation, majority of Chinese banks included in these two databases are observed to display missing values for these board-level variables during the sample period. To illustrate, for the variable of the total number of board directors, only 47 and 32 banks in our sample are able to download valid data for this variable (that can be utilised for estimation) from the Orbis Bank Focus Database and the SNL financial Platform, respectively. A similar situation applies to the executive compensation variable, for which only 16 sample banks can collect valid data from the SNL financial Platform for this variable, whereas the Orbis Bank Focus Database does not contain such information on Chinese banks.

When we attempt to collect corporate governance data from four Chinese databases[188] which contain financial and governance data on Chinese banks, our study is confronted with the same problem as above. Besides, manually collecting corporate governance data from each sample bank's annual reports also does not address this issue, as most of the sample Chinese rural commercial banks do not disclose corporate governance information in their financial statements. Nevertheless, Rowe, Shi and Wang (2011) and Luo (2015) question the quality of corporate governance data collected through this manual collection method due to reporting irregularities among Chinese banks, less standardisation in proxy statements, and language issues. Indeed, because of data availability and quality issues discussed above, this thesis does not consider board-related characteristics in bank performance analysis. In the future, a new dataset consisting of Chinese banks with access to high quality and valid corporate governance data should be created by us in order to examine the potential impacts of board-related characteristics on banking performance.

[188] They are the China Stock Market and Accounting Research Database, Wind-Economic Database, China Center for Economic Research database and Shenzhen GTA Database.

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Appendix A

Table 7.1: Estimation results for equation (3.9) of Model 1 to Model 4.

	Model 1		Model 2		Model 3		Model 4	
	SE	Std. error	SE	Std. error	SE	Std. error	SE	Std. error
2005	0.926***	0.020	1.096***	0.038	1.120***	0.124	0.845***	0.021
2006	0.965***	0.017	1.143***	0.030	1.087***	0.065	0.923***	0.010
2007	1.011***	0.014	1.187***	0.025	1.172***	0.168	0.986***	0.009
2008	1.028***	0.012	1.255***	0.023	1.122***	0.112	0.998***	0.012
2009	1.005***	0.011	1.240***	0.020	1.086***	0.101	1.017***	0.010
2010	1.008***	0.009	1.249***	0.014	1.097***	0.116	1.024***	0.009
2011	1.025***	0.008	1.252***	0.012	1.102***	0.095	1.037***	0.007
2012	1.021***	0.007	1.232***	0.013	1.106***	0.089	1.037***	0.007
2013	1.009***	0.006	1.201***	0.011	1.115***	0.085	1.036***	0.007
2014	1.006***	0.005	1.188***	0.011	1.120***	0.077	1.034***	0.007
2015	1.001***	0.007	1.137***	0.012	1.118***	0.047	1.047***	0.009
Whole sample	1.009***	0.078	1.207***	0.143	1.113***	0.124	1.022***	0.086

*Note: *** significant at the 1% level.*
Scale elasticities are estimated through equation (3.9). All values are estimated at the mean of the data.
The t test is performed for SE estimates with the null hypothesis that the mean equals one.
See Table 3.12 for the definitions of Model 1, Model 2, Model 3 and Model 4.

Source: Author's own calculations

Table 7.2: Estimation results for equation (3.9) of Model 5 to Model 8.

	Model 5		Model 6		Model 7		Model 8	
	SE	Std. error	SE	Std. error	SE	Std. error	SE	Std. error
2005	1.329***	0.093	1.048***	0.045	1.431***	0.021	1.024***	0.070
2006	1.238***	0.128	1.033***	0.036	1.315***	0.025	1.008***	0.058
2007	1.158***	0.151	1.061***	0.028	1.215***	0.020	1.095***	0.057
2008	1.099***	0.181	1.101***	0.026	1.138***	0.023	1.052***	0.073
2009	0.978***	0.137	1.031***	0.023	1.000***	0.016	1.020***	0.041
2010	0.962***	0.151	1.022***	0.017	0.984***	0.020	1.022***	0.048
2011	0.967***	0.128	1.059***	0.016	0.997***	0.015	1.036***	0.055
2012	0.977***	0.141	1.054***	0.016	1.014***	0.012	1.048***	0.060
2013	0.997***	0.121	1.038***	0.014	1.043***	0.012	1.051***	0.061
2014	1.060***	0.126	1.068***	0.013	1.087***	0.013	1.048***	0.051
2015	1.125***	0.119	1.068***	0.014	1.147***	0.012	1.039***	0.054
Whole sample	1.041***	0.159	1.054***	0.156	1.076***	0.169	1.040***	0.151

*Note: *** significant at the 1% level.*
Scale elasticities are estimated through equation (3.9). All values are estimated at the mean of the data.
The t test is performed for SE estimates with the null hypothesis that the mean equals one.
See Table 3.12 for the definitions of Model 5, Model 6, Model 7 and Model 8.

Source: Author’s own calculations

Table 7.3: Estimation results for equation (3.17) of Model 1 to Model 4.

	Model 1		Model 2		Model 3		Model 4	
	SI	Std. error	SI	Std. error	SI	Std. error	SI	Std. error
2005	5.87%	1.195	5.64%	1.564	8.61%	1.165	8.47%	3.377
2006	3.54%	0.686	6.40%	1.507	3.18%	0.581	1.90%	0.332
2007	3.67%	1.275	8.98%	1.885	18.12%	3.317	0.72%	0.195
2008	3.82%	0.984	14.80%	2.205	8.41%	1.243	2.36%	1.356
2009	3.50%	0.685	12.90%	1.927	5.31%	0.183	1.39%	0.398
2010	2.55%	0.538	11.40%	1.316	7.30%	0.251	1.47%	0.439
2011	2.70%	0.474	11.70%	1.216	5.75%	0.177	1.30%	0.264
2012	2.23%	0.413	10.96%	1.198	5.73%	0.19	1.75%	0.602
2013	1.83%	0.497	8.34%	0.906	5.97%	0.17	1.73%	0.542
2014	1.51%	0.204	7.40%	0.660	5.92%	0.191	1.52%	0.209
2015	2.54%	0.780	4.91%	0.577	4.39%	0.640	2.81%	0.783
Whole sample	2.59%	5.786	9.43%	11.629	7.15%	12.196	1.93%	6.167

See Table 3.12 for the definitions of Model 1, Model 2, Model 3 and Model 4.

Source: Author’s own calculations

Table 7.4: Estimation results for equation (3.17) of Model 5 to Model 8.

	Model 5		Model 6		Model 7		Model 8	
	SI	Std. error	SI	Std. error	SI	Std. error	SI	Std. error
2005	19.77%	12.398	9.09%	2.975	18.40%	5.294	4.69%	0.846
2006	12.15%	12.310	6.33%	1.394	17.09%	4.400	1.96%	0.382
2007	8.22%	15.818	7.44%	1.314	13.44%	2.108	16.63%	3.344
2008	7.10%	11.401	10.76%	1.866	11.36%	2.699	8.12%	0.317
2009	2.98%	3.579	7.84%	1.128	2.96%	0.507	5.67%	0.231
2010	3.92%	7.472	4.56%	0.959	7.07%	1.426	7.57%	0.847
2011	2.75%	4.540	6.28%	1.322	4.81%	0.970	5.28%	0.716
2012	3.31%	7.548	6.35%	0.986	3.73%	0.837	4.86%	0.737
2013	2.28%	3.408	4.38%	0.579	4.30%	0.772	5.47%	0.507
2014	3.08%	4.796	5.08%	0.561	6.52%	1.043	4.33%	0.243
2015	4.82%	7.349	5.08%	0.657	8.57%	1.162	1.52%	0.237
Whole sample	4.42%	8.098	6.13%	9.100	7.81%	14.037	6.01%	11.146

See Table 3.12 for the definitions of Model 5, Model 6, Model 7 and Model 8.

Source: Author’s own calculations

Table 7.5: Evolution of scale economies, Model 5.

Banks	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
1				0.80	0.72	0.73	0.74	0.76	0.80	0.88	0.97
2							0.91	0.98	0.94	0.99	1.11
3								0.90			
4	1.33	1.17	1.08	0.97	0.88	0.80	0.80	0.85	0.90	0.97	1.04
5						1.05	1.06	1.06	1.04	1.10	1.34
6						0.84	0.77	0.75	0.79	0.91	
7						0.94	0.93	0.93	0.93	0.97	
8	1.21	1.11	1.00	0.90	0.83	0.83	0.82	0.85	0.89	0.98	1.07
9			1.20	1.06		0.96	1.00		1.00	1.02	1.11
10	1.33	1.18	1.05	0.93	0.84	0.83	0.85	0.89	0.93	1.02	1.10
11			1.26	1.11		0.87	0.89	0.86	0.90	1.05	1.21
12			1.25				0.92	1.00	1.10	1.14	1.16
13				0.95		0.84	0.88	0.95	1.00	1.03	1.13
14							1.17	1.18	1.16	1.24	1.33
15				1.35	1.14	1.18	1.08	1.09	1.09	1.16	1.21
16					0.95	0.83	0.91	0.90	0.92	0.99	1.05

17								0.93	0.87		
18					0.97	0.92	0.91	0.94	1.01	1.07	
19			1.19	1.08	0.97	0.89					
20										1.19	1.27
21							1.04	0.97	1.01	0.96	1.03
22							1.07	1.10			
23					1.06	1.01	1.00		0.99	1.09	1.12
24									1.15	1.15	
25	1.68			1.18	1.11						
26							1.04	1.09	1.07		1.15
27						0.92	0.97	1.01	0.97	1.01	
28								1.01			
29					1.21			1.14	1.10	1.17	1.22
30						0.99	0.93			1.05	1.07
31								1.06			
32			1.15	1.05	0.91	0.90	0.89	0.89	0.88	0.93	1.00
33	1.41	1.26	1.18	1.05	0.93	0.97	0.96	0.88			
34					1.07	0.95	0.95	0.94		1.02	1.14
35							1.13				
36			1.05	0.97	0.88	0.85	0.88	0.89	0.89	0.93	1.00

37									1.17	1.23	
38							1.07	1.06	1.06	1.09	1.18
39				1.33	1.15	1.02	1.05	1.08	1.09	1.17	1.23
40				0.98	0.88	0.84	0.88	0.88	0.91	0.99	1.03
41						0.99	0.88	0.88		1.00	1.09
42										1.17	1.23
43		1.36	1.29	1.18	1.16	1.08	1.07	1.04	1.06	1.11	1.17
44			1.28		0.92				0.98		1.07
45			1.65	1.28	1.14	1.13	1.18	1.12	1.14	1.19	1.16
46		1.39	1.24				1.08	0.96	0.95	1.02	1.08
47							0.90	0.93			
48					0.84	0.83	0.83	0.90	0.96	1.08	1.11
49	1.40								1.03	1.07	1.20
50						1.00	1.01	0.92		0.91	0.99
51								0.83	0.82	0.91	1.05
52	1.37	1.27	1.14	1.02	0.93	0.86	0.87	0.86	0.86	0.92	0.98
53	1.22	1.04	0.91	0.83	0.75	0.74	0.76	0.79	0.85	0.94	1.04
54			1.06	1.01	0.95	0.91	0.94	0.82	0.90	0.95	1.01
55	1.25	0.00	1.15	0.99	0.91	0.95	0.97	0.97	0.92	0.97	1.03
56	1.32	1.19	1.04	0.94	0.84	0.82	0.82	0.84	0.87	0.94	0.99

57	1.36	1.21	1.09		0.92	0.86	0.86	0.86	0.94	0.97	1.04
58					1.05		0.89	0.90	0.92	1.06	1.10
59				1.10	0.97	0.97	0.97	0.99	0.98	0.89	0.96
60				1.43				1.00	0.95	1.03	
61						0.93	0.88	0.89	0.93	0.98	1.03
62								0.91	0.91	0.94	1.03
63				0.90	0.72		0.75			0.82	0.87
64											1.09
65				1.34	1.18		0.91	0.94	0.99	1.02	1.09
66								1.57		1.40	
67						0.96					
68										1.19	1.26
69									1.16	1.17	
70			1.42	1.37		1.19	1.12	1.19	1.23	1.24	1.25
71				1.15	1.02	0.99	0.97	0.99	1.02	1.08	1.25
72			1.07	1.08	1.01	0.99	1.00	1.06	1.03	1.07	1.14
73										0.97	0.94
74							0.81		0.91	1.02	1.13
75								0.99	1.05	1.10	1.19
76						0.97	0.91	0.90	0.94		

77				1.00	0.96	0.94	0.91			0.98	1.01
78				0.91		0.74		0.78		0.82	0.97
79				1.85		1.53		1.20	1.11	1.16	1.40
80				1.34	1.16	1.01		1.04	1.11	1.10	1.25
81		1.45	1.35				1.02	1.10			
82			1.19	1.06	0.94	0.86	0.92	0.96	0.95	1.09	1.17
83				1.07	0.98	0.96	0.93	0.97	1.00	1.09	1.14
84	1.37	1.15	0.95	0.90	0.79	0.92	0.91	0.89	0.86	0.95	1.07
85									1.11	1.22	
86			1.10	1.05	0.96	0.91	0.93	0.94	1.02	0.99	1.02
87	1.17	1.04	0.90	0.82	0.73	0.72	0.73	0.77	0.84	0.94	1.04
88	1.25	1.10	0.99	0.92	0.91	0.86	0.86	0.84	0.80	0.86	0.94
89										1.31	1.36
90									1.12	1.18	
91						1.01	1.00		1.02	1.06	1.11
92			1.27		1.05	1.03	1.09	1.04	1.10	1.16	1.28
93							1.10	1.09	1.14	1.25	1.29
94									1.19	1.26	1.21
95			1.28	1.11	1.04						
96										1.18	

97	1.70										
98								0.87	0.89		
99							1.42	1.36			1.31
100				1.49		1.07	1.06	1.07	1.11	1.10	1.11
101					0.94	0.81					
102										1.10	1.20
103						1.27	1.10	1.13	1.17	1.17	1.24
104								0.89	1.01	1.12	1.16
105	1.54	1.40				1.07	1.09	1.07	1.08	1.12	1.18
106				1.48				1.02	0.99	1.00	1.13
107						1.18	1.13				
108		1.19	1.04	0.91	0.80	0.84	0.87	0.81	0.81	0.91	1.00
109								0.62	0.66	0.74	0.82
110					0.94	0.94					
111										1.22	1.27
112				1.24	1.15	1.06	1.09	1.10	1.12	1.20	
113				1.08	0.95	0.88					
114	1.35	1.25	1.08		0.88		0.85	0.84	0.83	0.90	0.97
115				1.03	0.99	0.98	0.98	1.01	1.06	1.09	1.15
116					0.99	0.97	0.97	0.93		1.02	1.04

117						2.03	2.04	2.00	1.26	1.34	1.27
118					1.23			0.95	0.97	0.91	1.04
119				1.14	0.00	0.94	0.92	0.97	0.95	0.95	1.03
120						1.20		0.96	1.06	0.99	1.10
121								1.06	1.00	1.08	1.16
122				1.47	1.27	0.97	0.94	0.97	0.97	1.02	1.15
123								1.01	0.96		
124							1.13	1.13	1.21	1.31	1.54
125							1.05	0.99	1.06	1.14	1.21
126										1.14	1.20
127		1.26	1.13	1.13			0.84	0.86	0.91	0.96	1.06
128			1.14				0.99	0.74	0.76	0.84	0.94
129							1.22	1.10	1.05		
130										1.13	1.12
131				1.31	1.05				0.95	1.03	1.14
132							1.06	1.19	1.19	1.22	
133										1.16	
134								1.16			
135											1.20

See Table 3.12 for the definition of Model 5.
Where bank 1: Agricultural Bank of China, 2: Allied Commercial Bank, 3: Australia and New Zealand Bank (China), 4: BNP Paribas (China), 5: Bank of Langfang, 6: Bank

of Beijing, 7: Bank of Cangzhou, 8: Bank of Changsha, 9: Bank of Chengdu, 10: Bank of China, 11: Bank of Chongqing, 12: Bank of Communications, 13: Bank of Dalian, 14: Bank of Deyang, 15: Bank of Dongguan, 16: Bank of East Asia (China), 17: Bank of Fuxin, 18: Bank of Guangzhou, 19: Bank of Guilin, 20: Bank of Guiyang, 21: Bank of Hangzhou, 22: Bank of Inner Mongolia, 23: Bank of Jiangsu, 24: Bank of Jilin, 25: Bank of Jinhua, 26: Bank of Jinhzou, 27: Bank of Jiujiang, 28: Bank of Lanzhou, 29: Bank of Liaoyang, 30: Bank of Luoyang, 31: Bank of Montreal (China), 32: Bank of Nanjing, 33: Bank of Ningbo, 34: Bank of Qingdao, 35: Bank of Rizhao, 36: Bank of Shanghai, 37: Bank of Shaoxing, 38: Bank of Suzhou, 39: Bank of Taizhou, 40: Bank of Tianjin, 41: Bank of Tokyo Mitsubishi UFJ (China), 42: Bank of Weifang, 43: Bank of Wenzhou, 44: Bank of XI'an, 45: Bank of Yingkou, 46: Bank of Zhengzhou, 47: Baoshang Bank, 48: Beijing Rural Commercial Bank, 49: Changshu Rural Commercial Bank, 50: Chengdu Rural Commercial Bank, 51: China Bohai Bank, 52: China CITIC Bank, 53: China Construction Bank, 54: China Everbright Bank, 55: China Guangfa Bank, 56: China Merchants Bank, 57: China Minsheng Banking, 58: China Resources Bank of Zhuhai, 59: China Zheshang Bank, 60: Chinese Mercantile Bank, 61: Chongqing Rural Commercial Bank, 62: Chongqing Three Gorges Bank, 63: Citibank (China), 64: Credit Agricole CIB (China), 65: DBS BANK (China), 66: Dah Sing Bank (China), 67: Dongguan Rural Commercial Bank, 68: Dongying Bank, 69: Foshan Rural Commercial Bank, 70: Fubon Bank (China), 71: Fudian Bank, 72: Fujian Haixia Bank, 73: Guangdong Huaxing Bank, 74: Guangdong Nanyue Bank, 75: Guangdong Shunde Rural Commercial Bank, 76: Guangxi Beibu Gulf Bank, 77: Guangzhou Rural Commercial Bank, 78: HSBC Bank (China), 79: Hana Bank (China), 80: Hang Seng Bank (China), 81: Hangzhou United Rural Commercial Bank, 82: Hankou Bank, 83: Harbin Bank, 84: Hua Xia Bank, 85: Hubei Bank Corporation, 86: Huishang Bank, 87: Industrial & Commercial Bank of China, 88: Industrial Bank, 89: Industrial Bank of Korea (China), 90: JP Morgan Chase Bank (China), 91: Jiangsu Haian Rural Commercial Bank, 92: Jiangsu Jiangnan Rural Commercial Bank, 93: Jiangsu Jiangyin Rural Commercial Bank, 94: Jiangsu Wujiang Rural Commercial Bank, 95: Jiangsu Zijin Rural Commercial Bank, 96: Jiangxi Bank, 97: Jilin Jiutai Rural Commercial Bank, 98: Longjiang Bank Corporation, 99: Metropolitan Bank (China), 100: Mizuho Bank (China), 101: Nanchong City Commercial Bank, 102: Nanhai Rural Commercial Bank, 103: Nanyang Commercial Bank (China), 104: Ningbo Commerce Bank, 105: Ningbo Yinzhou Rural Cooperative Bank, 106: OCBC Bank (China), 107: Panzhihua City Commercial Bank, 108: Ping An Bank, 109: Postal Savings Bank of China, 110: Qilu Bank, 111: Qingdao Rural Commercial Bank, 112: Qishang Bank, 113: Royal Bank of Scotland (China), 114: Shanghai Pudong Development Bank, 115: Shanghai Rural Commercial Bank, 116: Shengjing Bank, 117: Shinhan Bank (China), 118: Societe Generale (China), 119: Standard Chartered Bank (China), 120: Sumitomo Mitsui Bank(China), 121: Tianjin Binhai Rural Commercial Bank, 122: United Overseas Bank (China), 123: Weihai City Commercial Bank, 124: Wing Hang Bank (China), 125: Wuhan Rural Commercial Bank, 126: Wuxi Rural Commercial Bank, 127: Xiamen Bank, 128: Xiamen International Bank, 129: Xiamen Rural Commercial Bank, 130: Zhangjiakou City Commercial Bank, 131: Zhejiang Chouzhou Commercial Bank, 132: Zhejiang Mintai Commercial Bank, 133: Zhejiang Wenzhou Lucheng Rural Commercial Bank, 134: Zhongshan Rural Commercial Bank, 135: Zhuhai Rural Commercial Bank.

Table 7.6: Empirical findings when yearly systemic importance scores are added into baseline equation (3.23).

Explanatory variables	OLS – equation (3.23)	FE – equation (3.23)	GMM – equation (3.23)	GMM – equation (3.24)
	A	B	C	D
SE_{it-1}	0.739*** (0.023)	0.522*** (0.028)	0.568*** (0.067)	0.555*** (0.065)
SEC_{it}	-0.102*** (0.032)	-0.076 (0.050)	-0.075 (0.102)	-0.295*** (0.095)
$SFTF_{it}$	0.128** (0.062)	-0.135* (0.077)	-0.235 (0.357)	-0.195 (0.214)
LR_{it}	-0.419*** (0.088)	-0.663*** (0.119)	-1.186*** (0.447)	-0.998*** (0.334)
$LRsq_{it}$	0.514*** (0.128)	0.632*** (0.175)	1.176** (0.592)	0.924** (0.506)
LLP_{it}	0.147*** (0.026)	0.117*** (0.029)	0.342** (0.147)	0.319*** (0.099)
$T1_{it}$	0.054 (0.062)	0.068 (0.140)	0.280 (0.397)	0.517 (0.415)
$SCORE_{it}$				-4.369*** (1.171)
$T1_{it} * SCORE_{it}$				33.633*** (10.288)
_cons	0.328*** (0.032)	0.553*** (0.039)	0.633*** (0.102)	0.609*** (0.131)
R-sq (overall):	0.753	0.709		
Breusch-Pagan	0.000			
Modified Wald test		0.000		

Number of IVs (groups)		63(118)	81(118)
Hansen-J-statistics		0.269	0.319
Difference-in-Hansen test (SE_{it-1})		0.530	0.624
Difference-in-Hansen test for levels equation		0.684	0.630
AR (1)		0.008	0.039
AR (2)		0.847	0.659

**Correlation is statistically significantly different from zero at the 10% level, **Correlation is statistically significantly different from zero at the 5% level, ***Correlation is statistically significantly different from zero at the 1% level. Standard errors are in parenthesis.*

SE_{it-1}: the autoregressive term, SEC_{it}: the securities to total assets ratio (%); $SFTF_{it}$: the short-term funding to total funding ratio (%); LR_{it}: the liquid assets to total customer deposits ratio (%); $LRsq_{it}$: the quadratic term of LR_{it}, LLP_{it}: the loan loss provision to total loans ratio (%), $T1_{it}$: the Tier 1 regulatory capital ratio (measured as the Tier 1 capital minus regulatory deductions as a percentage of bank risk-weighted assets), $SCORE_{it}$: yearly systemic importance scores, and $T1_{it} * SCORE_{it}$: the interaction term of $T1_{it}$ and $SCORE_{it}$.

Column A shows the estimation result of the dynamic base model as in equation (3.23) through the ordinary least squares (OLS) approach, column B is the estimation result of the dynamic base model as in equation (3.23) through the fixed effects approach, column C presents the estimation result of the dynamic base model as in equation (3.23) through a two-step System Generalised Method of Moments approach, column D is the estimation result of the dynamic base model as in equation (3.23) through a two-step System Generalised Method of Moments approach by adding on the yearly systemic importance scores and its interaction term with the Tier 1 regulatory capital ratio.

R-sq represents the R squared value (overall) to show the fitness of the OLS and FE estimation, Hansen-J-statistics tests the joint validity of all instrumental variables included, Difference-in-Hansen test confirms the validity of specified subsets instruments, AR (1) and AR (2) are the Arellano-Bond test for checking the assumption of no autocorrelation in error terms.

Appendix B

Table 8.1: Estimation results for equation (4.22).

Year	SI	Std. error
2005	12.28%	7.64
2006	12.98%	7.82
2007	9.08%	3.35
2008	11.19%	2.70
2009	6.49%	2.11
2010	6.23%	1.64
2011	7.85%	1.47
2012	8.77%	1.29
2013	10.22%	1.59
2014	9.90%	1.14
2015	10.06%	1.08
whole sample	7.22%	4.72

SI (scale inefficiency) is estimated through equation (4.22). All values are estimated at the mean of the data.

Table 8.2: Estimated cost parameters for equation (4.13).

	Coefficient	Std. error		Coefficient	Std. error
lnp1	-0.035	0.019	*lneqlnp3*	0.078	0.036
lnp2	0.405	0.018	*lneqlny1*	-0.210	0.024
lnp3	0.064	0.022	*lneqlny2*	0.113	0.014
lny1	0.189	0.031	*lneqlny3*	0.011	0.017
lny2	-0.217	0.028	*lnnpl*	0.010	0.007
lny3	0.374	0.041	*lnnpllnnpl*	0.005	0.003
lnp1lnp1	0.009	0.037	*lnllp*	0.028	0.009
lnp2lnp2	-0.272	0.030	*lnllplnllp*	0.007	0.003
lnp3lnp3	-0.042	0.039	*lnnpllnp1*	0.034	0.014
lnp1lnp2	0.607	0.021	*lnnpllnp2*	-0.001	0.012
lnp1lnp3	0.159	0.009	*lnnpllnp3*	-0.049	0.017
lnp2lnp3	0.114	0.010	*lnnpllny1*	-0.010	0.025
lny1lny1	0.122	0.020	*lnnpllny2*	0.007	0.009
lny2lny2	0.043	0.003	*lnnpllny3*	0.027	0.019
lny3lny3	0.045	0.006	*lnllplnp1*	-0.004	0.019
lny1lny2	-0.051	0.009	*lnllplnp2*	0.041	0.012
lny1lny3	-0.058	0.011	*lnllplnp3*	0.014	0.019
lny2lny3	0.002	0.008	*lnllplny1*	-0.003	0.024
lny1lnp1	-0.050	0.049	*lnllplny2*	0.037	0.014
lny1lnp2	-0.116	0.031	*lnllplny3*	-0.042	0.017
lny1lnp3	0.067	0.052	*t*	0.054	0.017
lny2lnp1	0.014	0.018	*t2*	-0.016	0.003
lny2lnp2	0.066	0.008	*Z1*	-0.063	0.015
lny2lnp3	0.001	0.019	*Z2*	-0.006	0.006
lny3lnp1	0.028	0.019	*Z3*	0.056	0.014
lny3lnp2	0.033	0.012	*Z4*	0.539	0.141
lny3lnp3	-0.047	0.020	*Z5*	-0.001	0.001
lneq	0.075	0.018	*sigma_u*	0.067	8.078
lneqlneq	-0.001	0.008	*sigma_v*	0.109	4.999
lneqlnp1	-0.075	0.033	*lambda*	0.619	13.076
lneqlnp2	-0.048	0.028			

*Note: *** significant at 1% critical level, ** significant at 5%, * significant at 10%.*
Where lnp1: Price of Labour (measured as Personnel Expenses/ Fixed Assets), lnp2: Total Value of Customer Deposits (measured as Total Interest Expenses/Total Customer Deposits), lnp3: Price of Capital (measured as Other Operating Expenses/Fixed Assets), lny1: Gross Loans, lny2: Other Earning Assets, lny3: Loans and Advances to Banks, lneq: Equity, lnllp: Loan Loss Provision, lnnpl: Non-performing Loans. All values are expressed in natural logarithms. And t: time trend term, t2: the square of time trend term.