Comparative Bank Financial Risk Management Models in Fintechs and Challenger Banks

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CANDIDATE DECLARATION

I hereby declare that:

1. I have not been enrolled for another award of the University, or other academic or professional organisation, whilst undertaking my research degree.
2. None of the material contained in the thesis has been used in any other submission for an academic award.
3. I am aware of and understand the University's policy on plagiarism and certify that this thesis is my own work. The use of all published or other sources of material consulted have been properly and fully acknowledged.
4. The work undertaken towards the thesis has been conducted in accordance with the SHU Principles of Integrity in Research and the SHU Research Ethics Policy.
5. The word count of the thesis is 80,000.

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ABSTRACT

Risk management in banking operations is a popular topic among researchers in the fields of management and banking. Due to developments in technology, research on financial technology has also become a hot topic. Banks and financial technology companies (fintechs) need to learn what risks impact their operations and how to manage these risks effectively. The aim of this study is to investigate the relationship between risk management and bank performance, compare it between traditional banks and challenger banks/fintechs, and make suggestions on how to improve performance by analysing historical data.

This thesis adopts a mixed-method approach, estimating risk variables and their impacts on bank performance through panel data regression models (random-effects and generalised method of moments) and conducting case studies to contribute to knowledge in theory and practice. This research investigates the relationship between five main types of risks (credit risk, market risk, liquidity and capital risk, reputational risk, and operational risk) and bank performance measured by three variables (ROA, ROE and EPS). This study confirms the importance of risk management in bank performance. For example, credit risk variables show negative impacts on all banks, which suggests that reducing credit risks could increase bank performance. Market risk variables are complex with both positive and negative effects on bank performance. Thus, banks should keep market risk at a balanced level to receive better performance. Moreover, bank performance could be increased by increasing liquidity, capital and reputation as well as reducing debt, operational issues and costs.

The contributions of this research include the enhancement of literature on the relationship between bank performance and risk management. Also, this research creates a greater awareness of risk management for challenger banks and fintechs. Moreover, it fills gaps in the literature by comparing results for traditional banks with those for challenger banks and fintechs. The results of this research offer new insights into risk management for both traditional banks and challenger banks and fintechs for

academics and have the potential to assist traditional banks and challenger banks and fintechs in managing their risks and improving their efficiency in practice.

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GLOSSARY

ASIC	Australian Securities and Investments Commission
APRA	Australian Prudential Regulation Authority
BCBS	Basel Committee on Banking Supervision
BI	Basic indicator approach
BIS	Bank for international settlements
CAR	Capital adequacy ratio
CBRC	China banking regulatory commission
C/I	Cost-to-income ratio
CR	Current ratio
D/A	Debt-to-asset ratio
D/E	Debt-to equity ratio
DWH	Durbin-Wu-Hausman test
EFTPOS	Electronic Fund Transfers at Point-of-Sale
EPS	Earnings per share
FCA	Financial conduct authority
FDIC	Federal Deposit Insurance Corporation (US)
Fintech	Financial technology
Fintechs	Financial technology companies
GMM	Generalised Method of Moments
GFHI	Global Fintech Hub Index
IRB	Internal ratings-based approaches
LCR	Liquidity coverage ratio
LoanR	Loan loss ratio (Total)
LSDV	Least squares dummy variable
NCO	Net charge-off rate
NIM	Net Interest margin
NPL	Non-performing loan ratio
NSFR	Net stable funding ratio
NYSE	New York stock exchange
ORP	Operational risk percentage
PRA	Prudential Regulation Authority
QR	Quick ratio
RADI	Restricted authorised deposit-taking institution
ROA	Return on Asset
ROE	Return on Equity
RWA	Risk-weighted assets
SA	Standardised approach
T1	Tier one capital ratio
VaR	Value at risk (Total)
VIF	Variance inflation factor

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PUBLISHED WORK

1) Zhao, K., (2018). Comparative Bank Financial Risk Management in Fintechs and Challenger Banks, presented at the MERI Research Symposium (Sheffield Hallam University).

CHAPTER ONE

INTRODUCTION

1.1 Introduction

The financial environment has changed since the last century. Financial technology innovations, increased global connections, several financial crises, and customer behaviour are all changing the ways banks provide services. With the complexity of the banking system growing and developing, these changes are becoming ever more demanding. Indeed, these changes have forced banks and financial companies to build more operational channels and strengthen their risk management (Cortiñas et al., 2010).

In more detail, the banking system has also faced different challenges through these changes. For example, fintechs are built to compete with traditional banks. The word 'Fintechs' is short for financial technology companies, and can also be seen as a type of challenger banks. In practice, fintechs cover many financial areas (e.g. banking, insurance and logistics). In this research, we only focused on those who operate bank related business more digitally and which were established recently. They have gained ground in the banking sector. Indeed, they provide similar banking services but mainly using digital means. In addition, consumer behaviour is shifting from physical transactions to digitisation. Traditionally, bank customers bought financial services and products through bank branches. With technological improvements, these services can be applied for through fintechs, changing the ways customers obtain these products and services.

Another reason for fintech development is the impacts of the last financial crisis, where traditional banks did not perform well, some of them even went bankrupt. Fintechs used this opportunity to reach more of the marketplace. However, after the crisis, traditional banks were required to have better risk management. Fintechs also did not perform as well as expected, where the main reason for which could be a high-risk approach in their management.

In order to have a better understanding of banks' and fintechs' performance through risk management, this research focuses on the risk variables and their impacts, based on the results available in the banks' semi-annually documented reports. With the analysis of three different countries for both traditional banks and fintechs, this research provides comparisons among these countries and bank types. This chapter gives an introductory overview of the thesis. It starts with an explanation of the research rationale. Then it provides the research aims, questions and objectives. The expected research contributions and methodology adopted are listed, followed by an outline of the organisation of the thesis.

1.2 Rationale of the research

The relationship between risk management and bank performance has been widely studied in the literature. Some studies focused on bank risk management, e.g. Bessis & O'Kelly (2015), Calomiris & Carlson (2016) and Docherty & Viort (2014). Indeed, Calomiris & Carlson (2016) analysed US bank risks from the 1890s by using regression models, while Bessis & O'Kelly (2015) focused on general risk management for the global banking system. Moreover, Docherty & Viort (2014) explained the consequence of risk management failure and regulation related to risk management by applying case studies in the UK, US, Canada and Australia, which also provided literature links to this thesis. Some other studies centred on the relationship between bank risk management and their performance by using panel data analysis, e.g. Anggaredho & Rokhim (2017), Fu & Heffernan (2006), Geng et al. (2016) and Hryckiewicz & Kozlowski (2017). In more detail, Fu & Heffernan (2009) investigated liquidity risk and its effect on Chinese traditional banks. Geng et al. (2016) concentrated on interest rate risk and its influence on Chinese traditional banks. Hryckiewicz & Kozlowski (2017) focused more on the impacts of the financial crisis on banks from 65 countries, while Anggaredho & Rokhim (2017) only investigated Indonesian banks.

However, due to the fact that fintechs are a relatively new area in the banking industry, there are only limited existing studies. Examples include the work of Chishti & Barberis

(2016) who studied the general development of the fintech industry as well as the studies of Francis et al. (2012) and Barberis & Arner (2016) who examined the value of bank innovation in the US and China, respectively. Other relevant studies include those of Aldriges & Krawciw (2017), Kotarba (2016) and Yurcan (2018), all of whom investigated risk management in fintechs.

With a holistic view, this research will review the literature on risk management in both traditional banks and fintechs. Following similar statistical methods and case studies found in the literature, this research will apply an analysis based on panel data regression models and case studies. Through comparisons, this thesis will examine the differences between fintechs and traditional banks, together with the differences shown among three different countries. It is important that banks, managers and investors can predict future performance based on their risk management performance using the regression models. The results will add new insight into banks' and fintechs' current models and enable banks to manage their risks to achieve better operations and improved financial performance.

1.3 Research aims, questions and objectives

The principal research aims are:

To investigate the risk management of banks and evaluate bank performance through statistical models; To examine how different types of risks affect the performance of traditional banks and fintechs; To compare the differences between countries and between traditional banks and fintechs and to provide a more comprehensive view of banks' risk management.

Based on the research aims, this study aims to answer the following research questions:

1. What are the critical characteristics of bank risk management variables, and how can we use them to analyse bank performance through bank data?

2. What differences are shown between traditional banks and challenger banks and fintechs in their risk management?

3. What differences exist among three different countries in risk management and bank performance, and how well did these countries react to the last financial crisis?

4. Through the analysis, what should these banks and fintechs do to improve risk management for future challenges?

According to Jogulu and Pansiri (2011), a step by step approach allows a more comprehensive study that answers the research question better. Thus, this study aims to address the following research objectives:

1. To understand key characteristics of risk management (e.g. risk types, variables and measurement, and legalisations) in the banking industry through extensive literature reviewing.

2. To investigate traditional banks and challenger banks and fintechs in the banking industry (e.g. growth, performance and risk management) by collecting data from interim and annual reports.

3. To use appropriate statistical models to analyse the performance of traditional banks and challenger banks and fintechs through the collected risk management variables.

4. To compare the differences between traditional banks and challenger banks and fintechs and between countries to highlight the pros and cons of risk management and performance.

5. Based on the results, to apply suggestions and provide recommendations for traditional banks and challenger banks and fintechs to improve performance.

1.4 Expected Contributions to Knowledge

This research will contribute to the literature in three ways. First, this research is unique because it analyses risk variables related not only to traditional banks but also to fintechs using panel data regression models. Previous literature, such as Fu & Heffernan

(2009) and Geng et al. (2016), only focused on Chinese traditional banks. Their work only investigates risk management in Chinese traditional banks from 1985 to 2002 and 2001 to 2012, respectively. Based on their suggestions, the importance of studying the years after 2012, for other countries and for another type of bank is clear. These will all be addressed in this thesis. We investigate risk management and its impact on both traditional banks and fintechs in 2013-2017 for three countries (China, the UK and Australia).

Moreover, there is limited existing literature related to fintechs. The analysis of this literature provided a background explaination for fintechs' risk management and performance, such as Hong et al. (2014) and Xu et al. (2014). Because of this, this research creates a better risk management awareness for fintechs, thus allowing us to solve bank operational problems as well. Thirdly, in an original way, we compare the results of traditional banks to those of fintechs, thereby, adding to the existing literature. Also, this research applies case studies in both traditional banks and fintechs to support the analysis from the panel data regression models. Therefore, this study provides a relatively comprehensive analysis of bank performance and risk management.

Thus, this research is suitable for PhD level because it requires an in-depth understanding and knowledge of banking risk management, financial innovations in the current financial environment, and the new banking area of challenger banks and fintechs. It will also provide comparative case studies of China, the UK and Australia. This research attempts to fill the gaps in risk management analysis of fintechs and comparisons between traditional banks and fintechs between countries. Also, the research results and research-developed models have useful implications in practice.

1.5 Research methodology overview

The research follows a combination of quantitative and qualitative approaches to identify the critical risk factors of traditional banks and challenger banks and fintechs and their impacts on bank performance. The quantitative approach involves numerical measurement and analysis, and the qualitative approach involves a textual description of the research (Kothari & Garg, 2014). Although it seems like two different approaches, in practice, these can be combined in a mixed-methods study (Easterby-Smith et al., 2002).

Before applying the quantitative and qualitative approaches, we start from a philosophical perspective. We contextualise the situation with the investigation of risk management and its impacts on both types of banks in the literature review in Chapter 2. Then, we use financial reports and case studies of Chinese, the UK and Australia banks to collect quantitative and qualitative data. Next, we collect and analyse information from bank financial reports, looking for evidence of risk management and its impact on bank performance. Similar to Docherty & Viort (2014), we use representative samples to address case studies which can illustrate the results achieved from our panel data regression models.

1.6 Outline of the thesis

This thesis is organised into seven chapters. A diagrammatic outline is presented in Figure 1.1, which shows the links between chapters. From Figure 1.1, we see the introductory chapter is followed by the chapter dealing with theoretical and statistical models in the literature in Chapter 2. Chapter 3 is the research methodology which provides links with the previous chapter. Chapter 4 contains our panel data regression analysis and our case studies follow in Chapter 5. We then discuss our findings in Chapter 6, and finally, our conclusions are presented in Chapter 7.

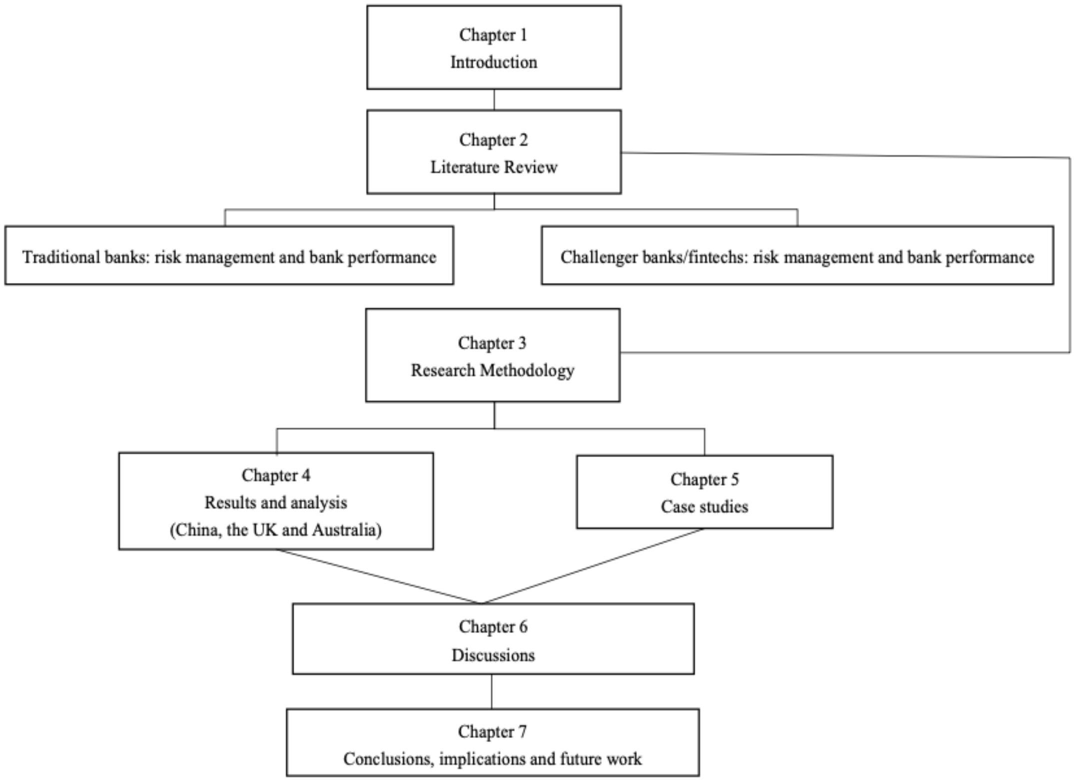


Figure 1.1 Diagrammatic framework of the thesis

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

For the last decades, globalisation and high-tech involvements have been the main trends of the global economy, while the financial system has played a vital role. At the same time, innovative financial products and services have increased competition and changed the global banking environment. Consumers now have more choices when buying financial services and products. Therefore, banks have to live in a more competitive environment (MacDonald & Koch, 2006). Moreover, the 2007-09 financial crisis had substantial impacts on every aspect of the global economy, especially in the banking industry. After the crisis, the Basel Committee released a tightening of financial regulation and risk management procedures for the banking industry. Therefore, bank risk management has become more critical than before.

In banking operations, the responsibility for managers is to maintain financial health by producing financial reports, investment activities, development strategies, and managing risks (Sokanu, 2015). Before the crisis, authorities paid more attention to the capital and market requirements which led to fierce competition between mortgage lenders. In order to earn more revenue and market share, mortgage lenders worked on subprime lending, which threatened the whole financial system and led to the global financial crisis. After the crisis, government authorities paid more attention to bank risk management. Understanding bank risk management is one of the best ways to see how banks work. For example, Koch and MacDonald (2015) discussed the nature of financial management, outlined the changes of economic environment especially in the US, indicated the measures for evaluating bank performance and risk management (SOAS, 2015). Bank regulation is another subject that needs to be understood. The basic idea of regulation is to ensure the safety of financial institutions and customers. For instance, Docherty and Viort (2014) described the regulations in the banking industry through time, and these regulations provided requirements for banks to follow and improve their performance.

Risks may occur at any time, but to address and solve every risk is very expensive, both in time and resources. So risk management is a continuous process. When managing risks, regulators, managers and analysts need to have identify, analyse, distinguish, and communicate skills (Greenfield, 2000). Therefore, identifying different types of risks could help managers to analyse, monitor, manage and reduce risks. Many risks exist in bank operations. Credit risk, market risk, liquidity and capital risk and operational risk are four of the main concerns for managers. Thus, in order to evaluate bank performance through risk management, the basic idea is to analyse risk variables from published or internal reports. For people outside of banks, the annual reports, government datasets and newspapers are direct ways to find risk variables.

Another change in the banking industry was financial innovation. Combined with the impact of the 2007-09 financial crisis, fintech became a developing and popular area in the bank industry. It brought more choices for consumers to buy financial services and products by offering more appropriate advice and lower-cost services. Challenger banks/fintechs have earned market share from traditional banks in recent years. For example, the bank card penetration rate of Chinese traditional banks dropped 2% when WeChat Pay was launched in 2013 (Wang, 2019). For the UK, fintechs for the first time outstripped net new lending to the UK SMEs by the traditional banks in 2017 (Arnold, 2017). For Australia, fintechs also added pressures to traditional banks. KPMG reported that P2P lending expanded 20 times from 2013-2015 (KPMG, 2017). Moreover, the deputy of governor of the Bank of Italy, Fabio Panetta, said that up to 60% of profits in traditional retail banking are threatened by fintechs (Cornell, 2018). All these examples prove that fintechs are competing with traditional banks in payments, lending and other financial services.

In addition, challenger banks/fintechs have been supported by government authorities in most countries after financial crisis. For example, the Bank of England planned to support and generalise fintechs in the banking industry (Binham & Arnold, 2016). Moreover, the Financial Conduct Authority (FCA) and the Prudential Regulation

Authority (PRA) approved start-ups bank licence applications, such as Atom Bank in 2016 (Mathuva, 2009). Similar situations happened in Australia as well, Australia Prudential Regulatory Authority (APRA) supported fintechs to compete with traditional banks through approving restricted authorised deposit-taking institution (RADI) licence (APRA, 2018). Fintechs in China showed an indisputable growth with government support, which was proved by the annual study of KPMG and H2 Ventures (Dunkley, 2016).

Besides the knowledge of risk management, statistical skills are also needed in this research area. Much previous research had analysed bank performance through different data analysis methods and models. For example, Nakashima (2016) centred on the relationship between bank risk management and performance by using panel data analysis for two large-scale Japanese banks.

From this perspective, this chapter, therefore, aims to review literature related to bank risk management and fintechs. It helps to provide a guide concept to the research aims, objectives, questions and general issues to be discussed in this study. The ideal outcome of this literature review should reveal the existing research gaps and provide insights for further research in this field (Müller-Bloch & Kranz, 2015). Two of the most relevant key themes to review are developed in the following sections. In Section 2.2, the fundamental aspects of bank risk management are shown. Section 2.3 investigates the development of challenger banks/fintechs and how they performed in risk management. Finally, conclusion and research gaps are presented in Section 2.4.

2.2 Bank risk management and performance

2.2.1 Bank regulations – The Basel Accords and local financial regulations

Before considering bank risk management and performance, regulations for local and global financial systems need to be understood. The basic idea of the regulations is to ensure the safety of financial institutions with developing requirements. For instance, Docherty and Viort (2014) described the regulations in the banking industry through time, and how regulations helped banks improve their performance (Docherty & Viort, 2014).

The Basel Accords are banking supervision accords including a series of regulations which are published through the Basel Committee. The Basel Committee is an international organisation which consists of representatives of central banks from G20 plus major banking countries and locales. The Basel Committee is still continuously updating it to fit the global banking system better, and to date, it contains Basel I, II and III (BIS, 2017).

Based on different types of risks, the Basel Committee on Banking Supervision (BCBS) published a series of requirements for banks in July 1988 which were called Basel I. Capital and risk-weighting asset (RWA) were two critical components in it. To be more specific, capital of the bank consisted of core capital (tier one capital) (e.g. common stock, retained earnings and non-redeemable preferred stock) and supplementary capital (tier two capital) (e.g. undisclosed reserves, revaluation reserves, general loan-loss reserves, hybrid capital instruments, and subordinated debt), where banks need to maintain their core capital at a certain level to continue its operations. Figure 2.1 shows the five risk percentage levels in the RWA. In particular, one of the first documented requirements was that banks have to hold at least 6% tier one capital in its RWA (BIS, 1988; Docherty & Viort, 2014).

Risk-weight	Loans and investments
0%	Cash and OECD sovereign debt Short-term or rolling unfunded commitments
10%	Some public sector entities
20%	Bank in the OECD and short-term loans to non-OECD banks
50%	Residential mortgages Long-term unfunded commitments
100%	Most other assets, including corporate and retail lending; non-OECD governments and long-term loans to non-OECD banks; real estate and equity exposures

Figure 2. 1 Summary of RWA. Source: Docherty & Viort (2014), P120.

Due to market and property bubbles, banks suffered losses in the 1990s. As a result, the BCBS began to improve Basel I from 1997. In 2001, the BCBS published the new bank capital measurements and requirements framework and revised it from 2006-09, which is called Basel II. In Basel II, a multi-prong approach called the three-pillar framework was designed. The pillars included minimum capital requirements, supervisory review and market discipline. All these pillars were mutually dependent, which meant one pillar could not work without the other two. Pillar 1 was similar and more comprehensive than Basel I to assess bank risks. It applied measures including the Internal ratings-based (IRB) approaches, the standardised approach (SA) and the basic indicator (BI) approach to credit, market and operational risk. Pillar 2 covered risks that Pillar 1 does not address. Pillar 3 listed information, requirements, objectives, policies and techniques for all interested parties (BIS, 2006) (Docherty & Viort, 2014).

Because of the 2007-09 financial crisis, the BCBS had to improve Basel II in the aspects of bank liquidity and leverage. Basel III added 2% equity of Bank RWA and minimised bank leverage ratio to 3%. It also introduced two liquidity ratios which are liquidity coverage ratio (LCR) and net stable funding ratio (NSFR). Basel III further tightened risk management requirements to improve the ability of banks to face economic stress (BIS, 2011) (Docherty & Viort, 2014).

The three countries we are interested in (China, the UK, and Australia) are all important members of the G20 who have the right to set the rules during the Basel Accords' negotiating process. More specifically, the UK is one of the important leaders of Basel Committee since the beginning of the Basel Accords. Australia followed the UK during these years for the standard-setting process and became an active country in the Basel framework. China, on the other hand, was a latecomer to the liberal economic world. China has been engaged more in financial reform since the 2007-09 financial crisis. The key piece of the reform included by China is Basel III. Based on Knaack (2017), Basel III was the first global financial standard involving China at the negotiation table. Thus, with development of the global economy, more developing countries like China could play important roles in standard-setting progress. For our countries of interest, based on their different geographical and economic situations, all of them can apply different but useful suggestions to BCBS and BIS, which further demonstrates their essential roles in the design of the global banking system.

Furthermore, as most regulatory systems adopted the Basel Accords frameworks, they published local regulations to monitor whether the banking system followed Basel Accords. As all three countries are members of both the Basel Committee and the G20, they follow the Basel Accords when regulating and monitoring their financial systems. For the UK and Australia, their governments publish regulations to ensure the safety and profitability for financial institutions under the Basel Accords framework according to local finance environment (Leonida & Muzzupappa, 2017; RIS, 2012). For China, on the other hand, as China's banks lack good governance, China cannot run the same process as the UK and Australia. Therefore, China needs to rely more on international standards for future global expansion in financial services. Before the 2007-09 financial crisis, to avoid local financial institutions violating these rules, China began to modify its financial regulations to follow the Basel Accords after joining the WTO in 2001 (Zhou et al., 2018). After the 2007-09 financial crisis, China published local regulations that were even stricter than Basel III (Knaack, 2017).

2.2.2 Bank performance

Financial intermediaries, including banks, help funds flow from savers to borrowers. Basu (1971) defined banking finance as activities that plan, raise, control and administer the funds used in business. McMenamin (1999) provided a similar definition that financial management is aiming to achieve some particular goals or objectives by determining, acquiring, allocating, and utilising financial resources (McMenamin, 1999). In order to have a better understanding of the bank, it is essential to analyse and evaluate bank performance.

In practice, analysts usually begin the evaluation of banks with the financial data and ratios that can be found in the annual reports. By analysing these data, ratios and profitability can be found, and analysts can better predict the future of the bank. Balance sheets and income statements are two primary sources that banks supply in their annual or interim reports. The balance sheet provides the financial condition at a point of time, such as at the end day of each financial year; quarter or month. The income statement provides a summary of profitability during a period, such as one financial year; quarter or month (Bodie et al., 2014). Regulators usually require banks to provide reports on a quarterly; semi-annually or annually basis.

From the bank reports, the fundamental of earnings and potential problems can be seen and calculated. For example, in financial statements, return on equity (ROE) and return on asset (ROA) are shown and can be calculated. Different risk variables can also be found and calculated in the risk management section. Earnings per share (EPS) can also be found in the listed banks. The authorities also use these variables to monitor bank system performance.

ROE and ROA have been established for a long time. Cole (1972) used this model to analyse the performance of banks. By developing over time, ROE and ROA had become the most commonly used performance variables in banks. There is a procedure using ratio analysis to evaluate bank performance and measure bank profitability. The results show the percentage of net income of a bank in a financial year. Thus, banks can compare their current and historical performance in investments and earnings (MacDonld & Koch, 2006). Although calculating banks' ROE is straightforward, breaking down ROE into different components makes it easier to understand. For example, the DuPont formula, also known as the strategic profit model, breaks down ROE into the net profit margin, asset turnover and financial leverage. The changes in each component will influence the ROE, where analysts can find operational problems more easily (Bodie et al., 2014).

Analysts can put ROE and ROA into different regression models to measure the impact of different situations. For example, in Pakistan, adopting the e-banking service had a significant positive impact on ROE which meant the adoption of e-banking reduced the cost of bank operations and increased customer satisfaction and bank profitability (Rauf & Ismatullaevich, 2013). Erdogan (2016) presented panel logistic regression models containing different financial ratios (e.g. loan due ratio and cost to income ratio) to show that Turkish banks had poor performance (e.g. ROA) during the recent financial crisis. He presented the panel with both random logistic and pooled logistic regression models to test the results which provided a warning system for Turkish banks to avoid further failure.

As another important performance variable for banks, earnings per share (EPS) is calculated to represent their profits in the stock market. The result could be seen as an indicator of banks' profitability. All listed banks and fintechs are required to report their EPS so that investors and regulators can use it to predict the potential share market performance. Banks or fintechs with higher EPS are considered more profitable (Nasdaq, 2009). As another widely used variable, many previous studies focused on banks' EPS and the variables which could influence it. For example, Bhattacharyya and Purnanandam (2011) aimed to test how mortgage and systemic risk impacted US banks' EPS by collecting 278 US banks' data from 2000 to 2006. They built a fixed-effects regression model which showed that higher mortgage exposure boosted EPS from 2000 to 2006 and led to the 2007-09 financial crisis. Their results showed that a higher systemic risk level positively impacts the EPS and that a higher system risk level can help banks receive higher earnings, but also led to the financial crisis with extreme losses.

2.2.3 Bank risk management

Bank risk management has existed since the beginning of bank operations, and definitions vary with different people and time. For managers, the primary objective is to maximise the wealth of shareholders. In order to achieve this objective, risk management has to be considered through bank operations. It requires managers to make trade-off decisions between higher returns and risks taken. Furthermore, because of the 2007-09 financial crisis, risk management has become a critical area in banking management. Bessis and O'Kelly (2015) addressed and covered almost all aspects of risk management in banking. Aebi et al. (2012) analysed how corporate governance factors and risk factors influenced bank performance during the 2007-09 financial crisis.

In their study, the simple regression model is applied to different governance and risk factors that affected the ROE of US banks before and after the financial crisis. Through an analysis of each factor impacting ROE and other returns, they highlighted the importance of risk governance in banks. Duygun et al. (2013) researched challenges and data analysis after the financial crisis, reframing the industry to improve the understanding, which helped managers to improve their performance facing the next financial crisis.

As noted above, the reason for using annual reports is that according to the Basel Accords and bank risk management frameworks, besides internal reports, the annual report is a direct and efficient way for the public to know a bank's risk management performance. Besides the performance variables, bank reports also present risk variables for people to analyse. For example, Kwan & Eisenbeis (1997) tested the relationships between bank risk management (e.g., interest rate, credit risk-taking, and capitalisation) and bank operational performance efficiency from 1986 to 1995. Through collecting data from 352 US banks, four linear regression models were applied. They proved that poor bank risk management could cause inefficiency in bank performance, and they also found that credit risk, interest rate risk and capitalisation are jointly influenced by each other. Similarly, Calomiris & Carlson (2016) analysed US bank risks since the 1890s by using regression models to present risk management and performance of banks. Through analysing 206 US banks, they found that improved formal corporate governance and reduced risks can improve the asset and equity performance of US banks.

Rad (2016) investigated the risk management and control system, which used two case studies in European countries. Based on 31 interviews, he found out that the control system (e.g. Basel II risk management methods) maintained and helped to monitor both case studies' loan operating procedures. However, he only showed the importance of Basel II in the banks' risk management, not risks faced by banks in their operations, whereas Kwabena (2014) and Hussain and Shafi (2014) did show this. Kwabena (2014) studied the Ghana commercial bank as a case study to show the risks faced by the bank, especially credit risk, and how to manage them. His findings presented evidence of the importance of credit risk management under the risk management framework. He showed that there is a significant positive relationship between bank performance and credit risk management efficiency. Hussain and Shafi (2014) used an Indian bank as a case study to show the operational risk faced in bank operations. By interviewing the respondents, their analysis showed the benefits of efficient operational risk management (e.g. lower cost, higher competitive position, and higher stability of earnings) and the limitations in the Indian bank (e.g. lack of senior management involvement, a limited budget, and difficulty in cost-benefit analysis). Thus, they built an operational management framework to improve operational risk management for Indian banks.

For financial institutions, in order to manage risks more effectively, risks are divided into different types. Some of the typical types are discussed below.

- **Credit risk**

Lending is an important bank operational activity. Credit risks exist during the lending process because the borrower can fail to meet its obligations to repay banks (BCBS, 2000). The last financial crisis exposed some problems in bank credit management system, such as inefficient monitoring, lack of technological improvement, regulation and market changes, and management framework varying across institutions.

According to the Basel Accords, credit risk is defined as '*the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms*' (BCBS, 2000). Different types of assets and activities have different probabilities of failure. For example, loan losses are a typical credit risk for banks. Moreover, many banks operate some off-balance-sheet activities, which increases risks and adds difficulty in measuring them from the published data (MacDonld & Koch, 2006).

In order to establish a credit risk management system, bank analysts usually combine financial and non-financial variables by using different models and tools. For example, managers could use both judgmental methods (with experienced managers) together with statistical models (with quantitative data). In more detail, judgmental methods are based on assessors' experience and understanding, whereas statistical models use statistical inference or quantitative data, such as credit scoring (Brown & Moles, 2014). The basic idea of credit risk management is deciding whether to extend or refuse credit. It requires the manager to balance the gain or potential loss from taking credit risk.

With its importance, there are several variables related to credit risk shown in bank reports. The three main relevant variables in this research are non-performing loan ratio (NPL), net charge-off rate (NCO) and total loan loss ratio (LoanR). NPL is the ratio to show the loan defaults of over 90 days; NCO is the rate of bank write-off over its average outstanding loan, and LoanR shows every loss of the lending activities. All of these reflect different aspects under credit risks which provide a comprehensive view for people to analyse credit risks. For example, Geng et al. (2016) tested bank risks with the NPL and interest rate factors for Chinese banks. They used random-effects panel data regression models to show their results, where the interest rate factor was positively related to bank risk performance; the loan ratios had a negative relationship. The results suggested that reducing the bad loan ratio or lowering both interbank or central bank interest rates could help Chinese banks improve their performance. Similar to Geng et al. (2016), Bailey et al. (2011) studied credit loan and its effect on Chinese state-controlled banks. They used loan variables (e.g. repayment time, repayment amount and percentage) to test the performance of state-controlled banks (using ROE and ROA). The results showed that underperforming banks need to obtain more loans in order to maintain their banking operations. Both of the studies suggested that Chinese authorities should improve the effectiveness of borrowing and of monitoring of banks' risk management. Cortez et al. (2019) used random-effects panel data regression models to test the relationship between interest rate, bank performance and bank risks using quarterly data from 2008-2018 in Philippine banks. Similar to results of Geng et al. (2016) in China, their results suggested that policy rate and overnight lending facility rate have a significant negative effect on bank risks, and that bank performance (e.g. ROA) is also significantly negatively affected by bank risks in the Philippines.

Barth et al. (2018) used an autoregressive and random walk regression model to test if regulators could use NCO and bank loss to forecast future bank performance by using the data from four banks (two big & two small US banks) from 1991-2016. Their results confirmed NCO and historical bank loss could be used to predict future performance, which had political implications for bank regulators. For example, through analysing NCO and historical bank losses, regulators can obtain a better position when they need to decide supervisory actions for a particular bank or a set of banks having serious troubles.

With the influences of the last financial crisis, credit risk management under risk management attracted more attention. For instance, PwC (2011) published an article listing the problems that the financial crisis brought to financial institutions and provided a framework which can improve the credit management for financial institutions after the 2007-09 financial crisis (PwC, 2011). Agarwal (2011) investigated the trends and opportunities in credit risk management and found that banks need a more innovative method for credit risk management (Agarwal, 2011). Both PwC (2011) and Agarwal (2011) found these similar points and tried to address these problems. They reached the same solution, which was to add more innovative management methods into bank credit risk management, such as software services updates. PwC (2011) suggested a framework called the credit risk and performance reporting dashboard, while Agarwal (2011) conducted a survey to show that innovative management in the bank credit management system is a useful tool to improve efficiency.

Nurgaliyeva (2014) and Cana and Cinac (2016) investigated the same area (innovative credit risk management methods). Nurgaliveva (2014) analysed a new approach for credit risk management in banking with a case study in Kazakhstan (Nurgaliyeya, 2014). Cana and Cinca (2016) analysed different financial indicators in the risk appetite framework and presented a regression model for Europe (Cana & Cinca, 2016).

Moreover, some studies also combined credit risk with other risks. For example, Chi & Li (2017) built a random-effects panel data regression model to test whether credit risk and economic policy uncertainty had an impact on banking performance. By analysing data from four Chinese banks between 2000 and 2014, they showed that both risks had negative impacts on the banks' performance (e.g. ROA). Indeed, they showed that a reduction in credit risk or a reduction in the supply of credit could improve bank performance in China when economic policy uncertainty increases.

- **Market risk**

For banks, investment is another critical activity which can make a profit. Investment operates in an evolving and changing economic environment. Risk of losses could happen during an investment project for banks, traders and investors. This type of risk is called market risk. It is the risk of losses which are caused by market movement, such as interest rate risk, exchange rate risk and share market risk (Bhaduri et al., 2007; Brunnermeier & Pedersen, 2009). Market risk has been studied for a long time, such as, Artzner et al. (1999) who studied both market and nonmarket risks and also discussed the measurement of these risks.

There are three main sub-types of market risks: interest rate risk, currency risk, and share equity risk. Value at Risk (VaR) is mainly used to represent market risk. It can estimate the risks of an investment in a normal market situation. In bank risk management, VaR is defined as the probability of loss in a given portfolio and time. For example, under Basel II and III, banks are required to use a 99% VaR capital charge with their model, which can help them reduce the variability of RWA (Laurent et al., 2016).

Kerkhof et al. (2010) chose VaR to represent the market risk variable which addressed that VaR and excepted shortfall could be used together to measure the capital reserves for the market performance of the companies. Williams (2016) used VaR variables to test their impact on the return (ROA) of banks in Australia. The dataset came from 26 Australian banks from 2002 to 2014, and the random-effects panel data regression model was used to present the results. He found that the relationship between bank risk and revenue composition was changed before and after the 2007-09 financial crisis. for example, non-interest income was generally believed to increase risk level, but he showed some different results after the recent financial crisis as some non-interest income reduced risks.

- **Capital and Liquidity risk**

Similar to market risks, as capital traders and investors for investment, banks play an essential role in the financial system who provide market liquidity, and their availability of funding gives them the ability to make trades. The potential loss of part of the investment, which leads not a full return of the original bank capital, is called capital risk. Liquidity, as one of the most important capitals for banks, also needs to be managed carefully. Liquidity risks happen if banks cannot trade assets or buy or sell an investment quickly enough. A typical and undesirable result could be that bank liquidity suddenly dries up (BCBS, 2008). The 2007-09 financial crisis also exposed problems in bank risk management, such as weak capital and liquidity risk management and inefficient regulation monitoring. Thus, many financial institutions went bankrupt; for example, the most famous case is the Lehman Brothers bankruptcy (Docherty & Viort, 2014; Ruozi & Ferrari, 2013). After the financial crisis, new capital and liquidity requirements were discussed and published by the Basel Accords, which forced banks to increase their abilities with respect to capital and liquidity risk management.

Furthermore, according to the Basel Accords, the definition of capital and liquidity risk management in banks is '*the ability of a bank to fund increases in assets and meet obligations as they come due, without incurring unacceptable losses*' (BCBS, 2008). In addition, the US Federal Deposit Insurance Corporation (FDIC) also issued a guide for financial institutions to explain the importance of capital and liquidity risk management, and provided strategies for managers to follow during operations (FDIC, 2008). Based on Bhaduri et al. (2007), liquidity risk can be categorised into market liquidity and funding liquidity. According to Brunnermeier and Pedersen (2009), market liquidity and funding liquidity were mutually reinforcing under certain conditions, and they built a model linking these liquidities and providing testable predictions.

Because of the importance of capital and liquidity risk in the banking system, many studies focus on managing them. For example, Greenspan (1999) discussed and contributed to the standard of liquidity risk management for a country. Both DeYoung and Jang (2016) and Ippolitoa et al. (2016) analysed bank liquidity risk management, where DeYoung and Jang (2016) tested whether banks managed liquidity from 1992 to 2012 and Ippolitoa et al. (2016) provided a method to improve the liquidity risks. They both provided similar results, which were that large banks manage liquidity more efficiently under the Basel management framework, and liquidity risks influenced small banks more in the US and EU. Fu and Heffernan (2009) tested bank liquidity risks for Chinese banks' performance (ROA and ROE) from 1985 to 2002. They used random-effects panel data regression models to test 14 Chinese banks. Their results showed that the liquidity holding level was positively related to bank performance. The results suggested that increasing the liquidity holding ratio could help Chinese banks improve their performance.

Sharpe (1995) examined Australian trading banks performance in capital risk management. He selected variables from thirteen Australian banks' annual reports from 1967-1988. By applying fixed-effects panel data regression models, he tested how these banks performed regarding assets (ROA and profit) with ten capital ratios and fixed-effects dummies among these banks. It showed that in the 1960s to 1980s, capital risk factors were positively related to high expected profit banks and negatively related to low expected growth banks. His study provided evidence that Australian banks use an asymmetric information approach to optimal capital structure.

Moreover, there are studies focused on improving bank capital and liquidity risk management. For instance, Liang and Yang (2010) built a sub-optimisation model under an equilibrium liquidity management strategy. By using an equilibrium liquidity management strategy, they proved that Chinese banks could balance profit and liquidity during the crisis.

There are several variables shown in bank reports which can help analysts to analyse capital and liquidity risks. To be more precise, seven main relevant variables are provided for this research. With regard to the efficiency of a bank's liquidity risk management, quick ratio (QR) and current ratio (CR) can be found. QR shows a bank's short-term liquidity and its ability to repay the current liability and CR shows its ability to repay current liabilities with its current assets. The difference between them is that QR only tests the most liquid current asset while CR tests all current assets. Zhang (2011) used a logistic regression model to test 28 financial indicators, which included QR, liquidity coverage ratio (LCR), CR and cost-to-income ratio (C/I), on 64 Chinese banks' performance. He showed significant effects of these variables. His results proved that Chinese banks need to strengthen risk management with an early-warning system, more manager training and suitable bank regulations.

With regard to the financial strength of the banks, the tier one capital ratio (T1) and capital adequacy ratio (CAR) can be found. T1 is a measure of bank capitalisation, defined as the ratio of tier one capital to RWA, while the CAR shows the ratio of both tier one and tier two capital to RWA. Shaban and James (2018) studied the effects of ownership change and risk exposure to bank performance in Indonesia from 2005 to 2012. They selected different variables to represent various risks (e.g. NPL, NCO, T1, and C/I) and tested their effect on performance variables (e.g. ROA, ROE and net interest margin). Through analysis with fixed-effects panel data regression models, they showed that the state-owned banks were less profitable and riskier than a private and foreign bank in Indonesia. Epure & Lafuente (2015) studied credit risk, capital and liquidity risk (e.g. NPL and CAR), governance and their impacts on the bank performance (e.g. ROA and net interest margin) in Costa Rican banks during 1998 to 2012. Through applying a random-effects panel data regression model, they showed that the improvement of risk management efficiency could positively influence bank performance. For the corporate governance area, they showed that CEOs from outside could improve performance, rather than internal executive turnover.

With regard to the bank debt level, Debt-to-asset (D/A) and Debt-to-equity ratio (D/E) can be found. The difference between them is the denominator, where D/E is total debt over the total equity and D/A is over the total asset. Both Pinto and Joseph (2017) and

Siddik, Kabiraj and Joghee (2017) tested the impacts of debt level on bank performance and proved the significant negative impacts. In more detail, Pinto and Joseph (2017) examined 21 Indian banks from 2011 to 2015. They found that both D/A and D/E have a significant negative impact on bank return on capital through a simple regression model. Siddik, Kabiraj and Joghee (2017) tested 22 Bangladesh banks from 2005 to 2014. Their results indicated that D/A had a significant negative impact on ROA and ROE and a significant positive impact on EPS through applying pooled ordinary least squares regression models. Both of them suggested that banks should select an optimal debt level to achieve better bank performance.

The final variable is the liquidity coverage ratio (LCR), which shows highly liquid assets held by banks to meet short-term obligations, where a high ratio ensures banks have the necessary assets to survive any short-term liquidity disruptions. Diallo et al. (2015) analysed operational risk, as well as credit and liquidity risk, by testing the performance of Indonesian banks using a fixed-effects panel data regression model in the panel data analysis. They used NPL to represent credit risk, LCR to represent liquidity risk, and C/I to represent the operational risk. Their results showed that reducing credit and operational risk and increasing liquidity stabilisation could improve the performance of Indonesian banks.

- **Operational risk**

The expansion of the internet and social media, internal operating procedures and factors, human factors and external factors are all incentives led risks that occur in banks' operations. Any factors may go wrong, which will increase risks in financial institutions (Bank for International Settlements (BIS), 2006). According to the Basel Accords, operational risk is defined as '*the risk of loss resulting from inadequate or failed internal processes, people and systems or external events*' (BIS, 2006). Moreover, EU Solvency II (2007) also gives a definition for operational risk which is the risk of change in value because of failure of internal processes, people and system (CEA – Groupe Consultatif, 2007).

For a long period, operational risks were classified as residual risks in financial institutions. However, this situation changed after the 2007-09 financial crisis. For example, Chinese banks invested more in software and staff IT training to improve operational risk management (Xie et al., 2011; Zhang et al., 2011). Banks in Romania, the US, Bosnia and Herzegovina all improved their operational risk management by adding more big data and IT management skills (Dumescu et al., 2012; Kozarevic & Kozarevic, 2016; McLaughlin, 2013).

However, it is difficult to monitor and analyse all possible operational risks. Studies can only focus on one or perhaps a few points of operational risks. For example, Zhang et al. (2011) and Xie et al. (2011) both analysed operational risk control of Chinese commercial banks based on the Basel Accord II with a questionnaire and Monte Carlo Simulation, respectively. Through analysis, Zhang et al. (2011) suggested that Chinese commercial banks should build an IT platform which can integrate the management system, and train employees to improve operational risk management. Xie et al. (2011) identified the capital required to prepare Chinese banks for operational risk in the context of Basel II.

Although the operational risk is hard to monitor, there are still variables in bank reports that could be used to analyse operational risk. One is operational risk exposure. Under Basel II, the operational risk exposure for the banks is 15% of their gross income (BCBS, 2014). Analysts could use operational risks that have occurred as analysing variables, such as fluency or losses of occurring operational risk, to compare with the operational risk exposure to show the operational risk management performance. For example, Chernobai et al. (2011) examined operational risk by using a frequency model in US banks from 1980 to 2005. By analysing operational loss data, they linked operational risk to internal control environment management (e.g., corporate governance, bank size, reported losses and sensitivity to banking risk). These links indicated the importance of improving managerial methods for dealing with operational risk events.

Another variable is the C/I ratio, which shows the efficiency of a bank's operation. C/I represents the percentage of total costs to total income. As mentioned above, Diallo (2015) and Shaban and James (2018) also selected the C/I ratio to represent the operational risk to test its effects on bank performance. Both of them showed the importance of operational risk management in bank performance and suggested that the central bank should provide better risk models and that banks should follow regulation.

- **Reputational risks**

Reputational risk can be defined as the potential loss in finance, capital, values in society and marketing, which will damage a bank's reputation (Heery & Noon, 2017). It influences not only banks themselves but also their employees and partners. Xifra and Ordeix (2009) investigated reputational risks for Banco Santander in Spain after the 2007-09 financial crisis. Through the case study, they argued that Spanish banks are in a strong position not only because they did not invest in US subprime mortgage products, but also because they have a well-established reputational risk management system. Cheung et al. (2011) used the recorded percentage change of the bank's brand value as a representative factor to put into the regression and catalogued it as brand value change (BVC). Both studies showed the importance of considering reputational risk management in bank operations. It suggested that for a better analysis of bank performance, reputational risk is worth adding.

- **Interactions between risks**

During the 2007-09 financial crisis, risks showed interactions. The different types of risks could have reinforced each other and worsened the loss situation further. For example, the shortage of liquidity (high liquidity risk) and subprime loan loss (high credit risk) led to a global financial crisis (high market risk). Thus, some of the previous literature investigated interactions between risks through correlation analysis. For example, Htay & Salman (2013) investigated the relationship between liquidity risk, operational risk, credit risk and market risk for ten UK listed banks from 2002-11. Through correlation analysis, they found that there existed relationships between risk types. Each bank showed its own relationship between risk types, so an increase of liquidity risk might increase operational/credit/market risk for one bank but decrease operational/credit/market risk for another. In general, they found that liquidity risk influenced credit risk negatively but had a positive impact on market risk. For operational risks, liquidity risk showed both positive and negative impacts. Moreover, the correlations between these risks were not so high as to influence the selection of these risks as variables to analyse bank performance. Based on their findings, managers could control the risk level based on types. For example, if a bank has relatively low liquidity risk, and a high credit risk. Managers can modify their liquidity risk management strategy to take a higher risk, which could help them to reduce the credit risk during operations. Thus, they suggested that bankers should use correlations to manage risks based on different conditions.

Besides the interactions between risks with correlations, some previous literature investigated the influence of risks and their impact on bank performance. For example, Hakimi & Boukaira (2020) investigated the interactional relationship between operational risk, credit risk and liquidity risks as well as the impacts of these risks on bank performance in Tunisian banks from 2000 to 2017. Through correlation analysis - similar to Htay & Salman (2013) - they found out that moderate interactions existed between risks. Through random-effects panel data regression analysis, their results indicated that all risks influence bank performance (e.g. NIM) while reducing liquidity risk and operational capital and loan activity can help Tunisian banks increase their performance. Moreover, the interactions between operational risk and credit risk had a positive influence where the interaction between operational risk and liquidity risk had a negative influence but not a significant one. Thus, they suggested that policymakers should enhance banks' capital and loan activities, help banks to reduce liquidity problems, then stabilise the macroeconomic context, which would all help Tunisian banks perform better.

Thus, in a supervisory position, regulators and managers began to consider the interactions between risk types and integrated management methods. BIS (2009) explained the interactions between credit risk, market risk and liquidity risk in a global supervisory position. The report showed that liquidity risk interacted with market and credit risk through the horizon over which assets can be liquidated. The credit risk interacted with the market risk increased by overall risk exposure increases over time. Moreover, valuation uncertainties or other shocks (e.g. subprime loan crisis) can enhance credit risk, which would also have adverse effects on liquidity and market risk. It also suggested managers should try to identify conceptual and empirical relationships between these risks and then make management strategies. However, it is difficult to define joint risks and manage them. In both historical and practical management progress, risks have been measured and managed separately by types as well as economic capital against each risk type. The approach often encountered in practice in the banking industry nowadays, is to estimate each risk type separately and then aggregate them (BIS, 2009).

Therefore, based on previous literature and management suggestions based on Basel III, this study could examine the correlation between different types of risks to determine their interactions, then analyse them together to test their influence on bank performance and provide political suggestions.

2.3 Financial technology, challenger banks and fintechs

As a result of innovation in information and communication technologies, the financial system has evolved towards the digitisation of transactions. Fintech innovations have increased global connections but have also triggered challenges for the financial system. With the increasing and growing complexity of the banking system, these changes have forced financial institutions to build more operational channels and strengthen their risk management to survive under the challenging environment (Cortiñas et al., 2010).

The fundamental objective of bank risk management is to maximise the wealth of shareholders. The management skills addressed in different banks have similarities which are to follow the models and rules in the Basel Accords and local government strategies. At the same time, different banks keep an internal risk management model for managing specific risks faced by the bank. As a new type of bank, many challenger banks and fintechs still follow the same models as traditional banks but with slightly different focuses (Bree, 2016). In addition, because of the recent financial crisis, more regulations were added to financial institutions. Risk management has already been changed in the past decade and needs further changes.

Before we investigate in depth the fintech area, the definitions of fintech, challenger banks and fintech should be further clarified. As mentioned in Chapter one, fintech is a short term for 'financial technology' which represents using technology to deal with financial activities (Schuffel, 2016). In practice, fintechs operate in many areas, such as issuance, logistics and banking services. Moreover, challenger banks, from its literal meaning, are the banks built to challenge and compete with traditional banks, especially large ones. Some of the challenger banks may became established, earn their market share and finally become traditional banks. Then we could distinguish them from historic traditional banks by more fintech involvement, such as an online only banking system (Flinders, 2015). Based on these definitions, we could find out that modern challenger banks and fintech banks all apply similar services and operate in more digital ways than traditional banks. Thus, for this research, we treat them as one in the some and call them fintechs and challenger banks, which includes fintechs which operate bank-related business together with challenger banks which has been established recently and operate in more digital ways.

This section will firstly focus on the history of fintech. Secondly, similar to traditional banks, the related regulations will be studied. Then, fintech area performance will be presented. Finally, risk management related to fintechs and challenger banks will be listed.

2.3.1 History of fintech

Fintech is a rapidly growing area, which can be traced back to the 1900s (Hochstein, 2015). From its literal meaning, it can be explained as the use of technology to drive financial solutions. The development of fintech could be divided into three periods from the middle of the 19th century. The first period is from 1866 to 1967. Finance and technology were interlinked and mutually reinforcing. These technologies were mainly in the financial service industry, such as money and stock transactions for joint-stock, insurance and banking institutions. The foundations for fintech during these years formed a basis for the modern period (Moore, 2000).

Since the late 19^{th} century, technologies had been developed rapidly and global communications and trade had tightened, which led to the second development period of fintech. The second period is from 1967 to 2008. From the late 1960s, the electronic payment system became established in the banking system. For example, the Inter-bank computer Bureau for the UK and Inter-bank payment system for the US were established in 1968 and 1970, respectively. The society of worldwide inter-bank financial communications and the BCBS were also established in 1973 and 1975, respectively. All of these led to a series of international agreements in fintech and continued developing through time (BIS, 2018). In the second stage, many technologies were applied to the banking system, such as ATMs applicated globally. However, with the development of fintech, there were risks exposed in the banking and finance system, such as 'Black Monday' around the world in 1987, and the capital collapse and financial crisis around Asia and Russia in 1997-98 (Bookstaber, 2007; Buckley et al., 2016; Jorion, 2000).

The third period of fintech is from 2008 until the present day. During these years, with more involvement of technology in life, consumers began to shift their financial behaviour to digitalisation. Another trigger of the third stage of fintech was the 2007-09 financial crisis. As a result, costumers began not to trust banks with their finances as they had before. For example, in 2015, there were more people trusting fintechs than banks to deal with finance in the US, with only 28% of people having confidence in financial services supplied by banks (MEDICI Team, 2015). Further, because of their cheaper cost, many people choose fintechs instead of banks.

Fintech today are developing in different ways in developed countries and developing countries. In developed countries (e.g. the UK, the US and European countries), the fintech concentrated on and developed four main areas. Firstly, fintechs extended the financing transaction methods (such as algorithmic trading), financing mechanisms (such as P2P) and Robo-advisory services. All of these helped to extend finance and investment areas beyond that of traditional banks (Chappuis Halder & Co, 2015). Secondly, fintech helped managers to build better compliance systems to manage internal financial operations and risk management. Thirdly, as digitalisation developed, cybercrimes increased a lot. Cybersecurity became a major concern for governments, regulators, participants and customers. Thus, many fintechs were keen to create safer and better data security systems to protect their business. Finally, fintechs improved electronic payment systems for both domestic and cross-border payments. This helped with the development of infrastructure in IT and communication (Buckley et al., 2016).

In general, fintechs could offer new financial products to the existing consumers of traditional banks which threaten the operations of traditional banks. This is also shown in fintechs in developing countries. Most of the developing countries are in Asia and Africa, and government policy encouraged fintech development in these countries. In these regions, over 1.2 billion individuals were still unbanked in 2016. Not only traditional banks but also challenger banks and fintechs can supply services to these individuals (McLean, 1998; Buckley et al., 2016). With regards to Africa, its underdeveloped level of banking and financial services, combined with its speedy development of mobile phone use, has led to fintech development in Africa from the beginning of the 21st century. For example, a successful fintech M-Pesa from Kenya launched in 2007. Payments made through M-Pesa account for over 43% of Kenya's GDP (Runde, 2015; Safaricom, 2016). For the Asia region, the three main reasons that fintechs could develop well are: firstly, IT spending in Asian traditional banks was going at a slower speed than fintechs. Secondly, the efficiency of the state-owned banking system and branch network was worse than in developed countries and fintechs. Thirdly, the high rate of smartphone penetration in this region provided a good condition for fintechs' development (Aritomo et al., 2014). Because of the significant opportunities existing in the developing countries, many challenges and issues needed to be faced during these years (Buckley et al., 2016).

Besides the general history of the fintech, there are three countries we are interested in investigating. The first country is China. Unsurprisingly, as giant fintech unicorns (e.g. Alibaba, Baidu and Tencent) exist in China, Chinese cities obtained top spots in the Global Fintech Hub Index (GFHI) 2018. In more detail, Beijing is at in No.1, Shanghai No.3, Hangzhou No. 6 and Shenzhen No 7 (Fintech News, 2018). For these giants, their business covers almost every aspect of the fintech industry. For example, Alibaba has AntFinance in the fintech banking area, AliLogistics for fintech logistics and AliHealth for fintech insurance. Moreover, it also cooperates with well-developed traditional companies in the area. Besides the giants, there are also successful fintechs and challenger banks. For example, Yirendai (YRD), which was the first Chinese fintechs, joined the NYSE and was voted as amongst the top 10 safest and best Chinese fintechs in 2020 (ShitouFinance, 2020).

The second country is the UK. As a major financial centre of the world and one of the first countries to support and invest in fintech, London, UK obtained No.4 in the GFHI 2018 (Fintech News, 2018). Similar to China, the UK also has successful fintechs and challenger banks. For example, Atom bank became the first fintech bank with licence approved by the FCA in 2015 (Gulamhuseinwala, 2015). With its higher savings rates and good services, Atom attracted media attention and customers (Atom, 2019). Another example could be Starling bank, which was the first UK mobile-only current account operator and also got a bank licence in 2016. Together with its easily accessible business accounts, Starling showed its advantages and aimed to expand into Europe in 2020 (Rainmakrr, 2020) (Starling, 2019).

The last country is Australia. With its unique geographical position and being a hub of economic growth in the world (Australia continuously increased its GDP from 1991 until the influence of Covid-19 in 2020 (Xinhua, 2020)). Australia also plays an important role in the fintech industry, Sydney, Australia achieved No.8 in GFHI 2018 (Fintech News, 2018). Australia also has successful fintechs and challenger banks. Wisr, for example, was the first fintech to be publicly listed in Australia. With its faster and easier deals for lending, it grew rapidly (Wisr, 2019). Another example could be Tyro, which received its bank licence in 2005 and became the first fintech to do so. With its continuous growth over a decade, it became the largest EFTPOS provider in Australia (Tyro, 2018).

Thus, each of these three countries had at least one city in the top 10 fintech hubs around the world in 2018. In addition, they all have successful fintechs and challenger banks in the industry. So, each of these three countries has shown their high potential in the fintech area, which could let them become a strong driving force of the growth for global financial markets and economies.

A the most influential country in the world, the US also plays important role in the fintech industry. American cities obtained some high spots in the Global Fintech Hub Index (GFHI) 2018. In more detail, San Francisco stayed at No.2 and New York achieved No.5 (Fintech News, 2018). From this list, we can see that China's cities surpass American cities as the top fintech hubs. We can see that competition between China and the US is intense in fintech industry. The intense competition between China and the US is also showed in other economic and technological areas. In addition, based on Buckley et al. (2016), as a developed country, the US provided similar process to the UK in fintech development and management. Thus, although the US could be selected as a comparison country, we excluded it based on its intense relationship with China and its similar fintech development process compared to the UK.

2.3.2 Regulation development for fintechs

Until now, well-established financial institutions and regulators worked together to develop regulations through market consulting and investigations. However, new fintechs entered the financial industry without a compliance culture and without interacting with regulators. In many countries, laws and regulations are still in an uncertain situation. Thus, besides the regulations published for the banking and finance systems, regulators also need to understand the new trends of innovations and publish regulations to monitor and manage the fintechs.

As the leading country of fintech, the development of fintech regulations in the UK is worth investigating. Gulamhuseinwala (2015) said that the UK had the world's leading fintech policy environment. The FCA in the UK provides a supportive regulatory regime to all financial systems, especially to the fintech area after the financial crisis. For example, these policies had simplicity, transparency and an industry-led approach, including the approach for fintechs. Firstly, the FCA supported project innovation in business to develop financial technology. For example, the FCA approved Atom with a bank licence as the first fintech challenger bank in the UK, and it also approved three hundred innovative firms in 2015. Another approach was the FCA supplying a regulatory sandbox for fintech companies which were a 'safe space' for fintechs to test their innovative services and products. This 'safe space' helped fintechs test their innovations without immediate regulatory consequences (Gulamhuseinwala, 2015).

Moreover, as fintechs developed during these years, the FCA and the UK government finalised a series of regulations to support and monitor the fintech area. For example, the FCA published final rules to improve conduction and communication in fintech (including e-money) services on 1st February, 2019 and applied the regulations on 1st August, 2019. At the end of 2019, the panel of UK government's fintech delivery group would like to publish industry standards for fintech partnership, and the EU expert group is expected to publish its final report on financial innovation regulations (Linklaters, 2019). Figure 2.2 shows the general regulatory development of the EU/UK. It shows how the regulatory framework has developed and has become more comprehensive until February 2019 (KPMG, 2019). General regulatory development of the EU/UK for the rest of 2019 is presented in Figure 2.3. In addition, under the Covid-19 situation in 2020, programmes to develop greater fintech adoption, convergence and collaboration developed delays in the EU/UK. For example, regulators paid more attention to published regulatory plans (e.g. EU digital finance proposals, Fintech action plan and road map and European commission papers on digital finance), to see the current situation and add more rules. Crowdfunding Regulations are aimed to be published in October or November 2020 officially and will then apply in 2021 (Ashrst, 2020).

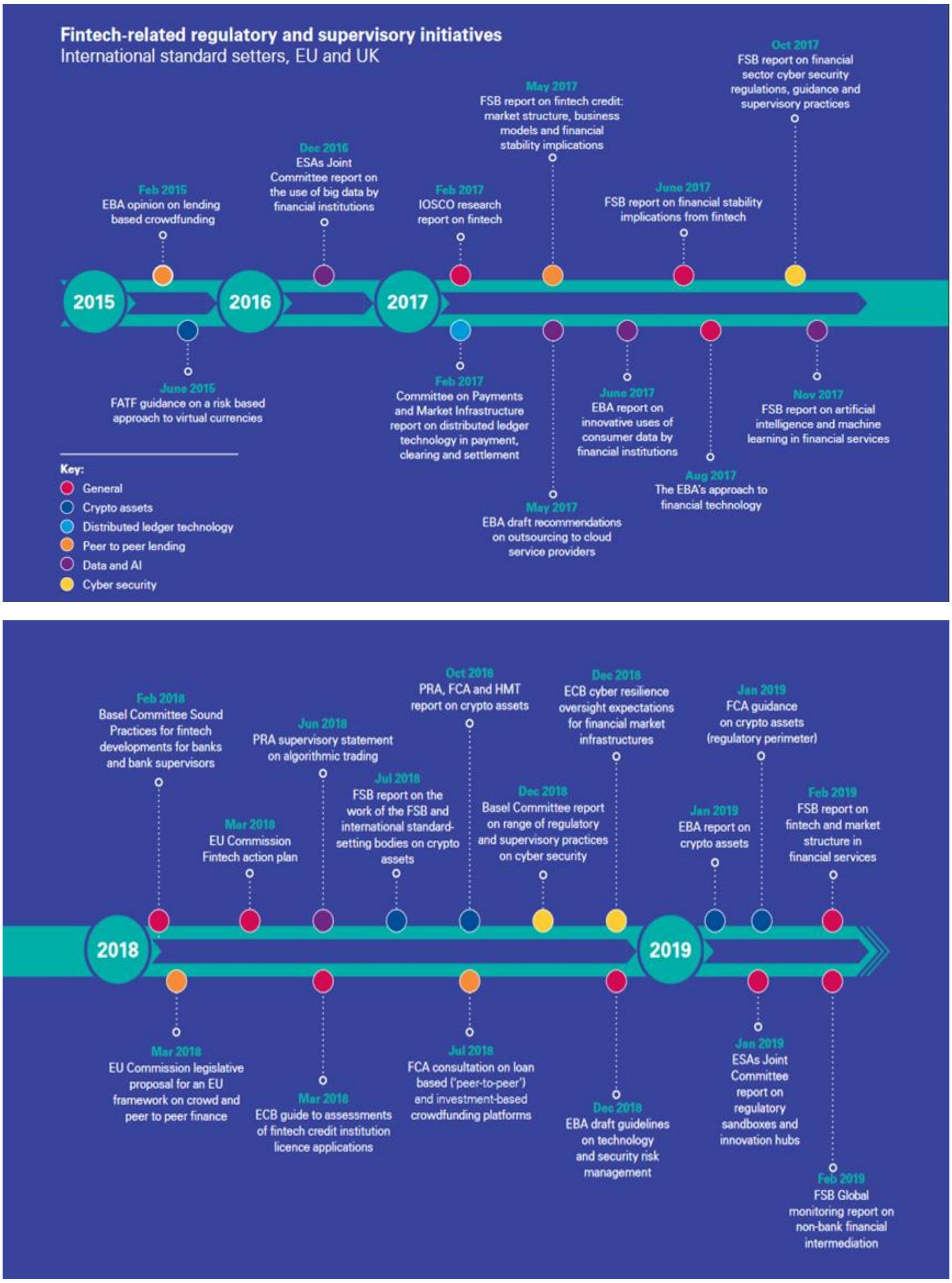


Figure 2.2 Fintech-related regulatory and supervisory initiatives. Source: KPMG (2019), P11-12.

March 19	12 March – BCBS publishes report on central bank digital currencies 13 March – FCA reports back on phase 1 of its digital regulatory reporting pilot 14 March – Online payment account providers to have in place the technical specifications of their access interfaces and the testing facilities for third party providers
April 19	29 April – FCA announces next steps for the Global Financial Innovation Network cross-border testing pilot
May 19	9 May – UK Jurisdiction Taskforce launches consultation on cryptoassets, DLT and smart contracts 28 May – FSB reports to the G20 on cyber incident response and recovery 29 May – FCA publishes call for input on a cross-sector sandbox 31 May – FSB reports on cryptoassets covering regulatory approaches and potential gaps
June 19	4 June – FCA publishes PS19/14 with finalised new rules for peer-to-peer lenders 6 June – FSB publishes report on the stability, regulatory and governance implications of decentralised fintech 20 June – Bank of England publishes Future of Finance report 25 June – FCA publishes report on the Global Financial Innovation Network (GFIN) 26 June – Council of the EU adopts a general approach to the proposed crowdfunding regulation 30 June – Bank for International Settlements (BIS) announces launch of Fintech Innovation Hub for central banks
July 19	8 July – EBA reports on the impact of fintech on payment institutions' and e-money institutions' business models 12 July – ESMA publishes report on the licensing of fintech business models in the EU
August 19	1 August – FCA rules on conduct and communications in payment services and e-money sectors apply
December 19	9 December – FCA PS19/14 rules and guidance for peer-to-peer lenders to apply 15 December – Most of the provisions of the cross-border payments regulation apply

Figure 2.3 Fintech UK and EU Regulatory Timeline 2019. Source: (Linklaters, 2019)

At the beginning stage of the fintech sector in China from 2006 to 2015, China's regulators applied a laissez-faire management approach to this newly established industry. The regulators were not concerned and refused to acknowledge the phenomenon of this industry. As a result, China's regulators did not publish legal rules or tools for these new financial and commercial practices, which caused free development in this sector (Ranchordas, 2015). At this regulation-free stage, problems arose with fintechs, such as liquidity shortage for payback, money and property fraud, and sudden run-away or shutdown fintechs. Because of the high volume of investors and problems that happened between 2005 and 2015, the protection issues of the Chinese fintech sector caused potential issues for the whole financial system in China (Shen, 2015). Thus, on 18th July 2015, regulators and the People's Bank of China issued the first official regulation on the fintech sector, called 'Guiding Opinions on Promoting the Development of Internet Finance' (People's Bank of China & Government of China, 2015).

After the first regulation on the fintech sector, regulators published a series of rules and additional regulations. The existing Chinese regulatory framework for the fintech sector was settled under a 'one plus three' approach. The 'one' is ‘Online Lending Measures 2016' which can be seen as the charter for online lending in China and outlines the requirements and disclosure practices that fintechs should follow. To be more specific, the 'one' firstly defined the legal position of the fintechs, especially fintech banks, and also established the central regulation system for the fintech sector. In addition, it focused more on risk management in fintechs operations. The 'three' are: 'The Fintech Recordation Act 2016', 'The Fund Depository Management 2017' and 'The Information Disclosure of Fintech 2017'. These provided detailed rules and requirements that fintechs needed to follow and gave investors ways to investigate the background of fintechs (Zhang, 2017).

Following the UK and China, Australia also put a lot into the fintech sector. As Australia collaborates with both China and the UK, it is also essential to look at the Australian regulations published during these years. Similar to the UK, the Australian Securities and Investments Commission (ASIC) also supplied a fintech regulatory sandbox which provided fintechs either flexibility in the law or fintech licensing exemptions in the financial services system (ASIC, 2019). In general, regulators in Australia applied equal regulations for fintechs and supported tech-focused business into the fintech market. Moreover, regulators helped fintechs broadly by offering informal guidance for regulatory understanding by building innovation hubs. ASIC also entered several cooperation agreements with other countries' regulators because of the cross-sharing of information on the fintech market (Reeves, 2019).

In general, besides the countries listed above, other countries also published a list of regulatory and supervisory documents relating to the fintech area. The regulatory which responses to risks related to fintechs had been lengthening, and it seems that the laws and regulations will continue developing in the coming years as fintech development and the adoption of fintech continues to grow.

2.3.3 Fintechs' performance and risk management

Having considered the history of fintech and regulations, this section will show the performance of challenger banks and fintechs. Financial innovation aims to produce new products, processes, services and organisations to reduce risks and costs and to increase benefits through using new financial technologies (Banka, 2013). The representative financial innovations in the banking industry include: online banking, online trading platforms, challenger banks and fintechs (Atkins, 2013).

The fundamental purpose of challenger banks and fintechs is to compete with traditional banks and use innovative methods to provide financial services (Lin, 2015). Although people are increasingly turning to digital ways to manage their money, challenger banks and fintechs still offer ways for their customers to pay in money at their branches to attract more customers. For example, Metrobank launched in 2010 and opened branches in London (Moneyfacts, 2016). Moreover, challenger banks and fintechs have focused more on consumers' needs from the outset than traditional banks by using data tools. There are some main advantages of fintechs. Firstly, fintechs have a direct online system for customers and investors. Secondly, fintechs have no boundaries between countries, which means no matter where consumers live, the financial services are accessible. In addition, many countries' governments encourage and support fintechs (Deloitte, 2019).

Because of their competitive advantages, the challenger banks and fintechs have developed. The continued growth of fintechs is illustrated by the improvement of their services and trading methods compared to traditional banks. However, people who work in challenger banks and fintechs need a mix of skills in technology, risk management, governance, and other bank operation skills. Until now, the performance of challenger banks and fintechs had not been as good as expected, and some of them operate inefficiently. Therefore, they still need to improve their performance in the competitive environment (Bouvier, 2015; Chishti & Barberis, 2016; Carey, 2017; Weyer, 2015).

The 2007-09 financial crisis was another trigger for paying attention to fintechs. It forced banks to expose some of their weaknesses and to take a critical look at their risk management (Kelly, 2017). It also provided an opportunity for challenger banks and fintechs to join the market. Government authorities transformed their attitudes from restrictions to support (Kiisel, 2014), for example, the UK challenger banks and fintechs took on important roles in financing the liquidity for SMEs based on government support. In 2013-14, they provided liquidity to SMEs to increase 14% of their assets (Paul, 2015).

Thus, based on their competitive advantages and government support, fintechs grew and gained market share compared to traditional banks. For example, in China, the adoption rate of fintechs was 69% at the end of 2017 and increased to 87% at the end of 2019, which was higher than most countries (EY, 2017; EY 2019). At the end of 2017, there are ten unicorn fintechs, thirty large fintechs and hundreds of small fintechs in China. In nearly ten years of development, Chinese fintechs gained 30% market share in the Chinese financial industry (Men, 2018). Xiang et al. (2017) also proved the development of Chinese fintechs from Chinese government data. They suggested that in order to keep developing fintechs in China, regulators and managers needed to improve risk management, build a better governance system, and strengthen customer protections. In the UK, fintechs and challenger banks also gained market share. The adoption rate of fintechs was 42% at the end of 2017 and increased to 71% at the end of 2019 (EY, 2017; EY 2019). Moreover, based on Crealoggix (2018), 14% of UK bank customers have at least one fintechs or challenger banks account across all ages and the number become 25% for millennials and gen-z individuals. However, fintech disruption in Australian traditional banking industry is limited. The adoption rate of fintechs was only 37% at the end of 2017 and increased to 58% at the end of 2019, which was lower than the other two countries (EY, 2017; EY 2019). Based on S&P Global (2020), the level of technology disruption in Australia is moderate, which is lower than in the UK (high) and China (very high). Fintechs in Australia only held 0.05% of system lending and 3% of the credit card market at the end of 2019. But the impact of fintechs on traditional banks are increasing with high development of the fintech industry in Australia. For example, investment in Australian fintechs increased from $259.5 million in 2017 to $1913 million in 2020(KPMG, 2020).

However, because the fintechs sector is relatively new, there few studies focus on testing their performance and influencing factors. Thus, any improvement in the area could help challenger banks/fintechs perform better in the competitive environment

(Carey, 2017).

Some studies investigated the adoption of fintechs, such as Broby & Karkkainen (2016), who investigated the development and adoption of fintechs in Scotland. They showed that the key drivers of fintechs were the reaction of government and consumers, and risk management performance. They suggested that the Scottish government and the traditional banking system should allocate specific resources to react to and assist with fintechs' development. Ryu (2018) used multi-variable regression models to test the risks and benefits of fintech adoption by analysing 244 fintech users. He showed that legal risks had the most significant negative effect, and convenience had the biggest positive effect. He showed that risk management influenced the users' selection and performance of fintech.

Some of the studies focused on different types of risks and different countries. Claessens et al. (2018) used simple regression analysis to examine credit risk management and its influence in fintech market performance in China, the US and the UK. Their results showed that credit risk management efficiency, customer and investor protection and fintech regulations all influence fintechs' performance. Improving these factors could help develop fintechs. Roeder et al. (2018) analysed credit risk, market risk and operational risk variables and their impact on fintechs' performance (total revenue) through applying multiple regression models to 221 fintechs worldwide. As a result, their model could help potential investors to determine the better fintechs to invest in in the future.

Hong et al. (2014) and Xu et al. (2014) studied Chinese fintechs' operations. Hong et al. (2014) focused on operational, regulatory and technological risks, while Xu et al. (2014) focused on liquidity and operational risks. These two studies suggested that managers and regulators need to establish a better framework to reduce these risks. For example, they suggested that the government could publish regulations for fintechs, which the Chinese government then did from 2015.

Moreover, the risk-return structure is different for different types of banking. Based on literature for risk management in fintechs and challenger banks (shown above) and in traditional banks (shown in Section 2.2.3), we could find that risks had different impacts based on type of risks. There is some literature showing risks that had different impacts on bank performance based on type. For example, Iannotta, Nocera and Sironi (2007) analysed 181 banks from 15 EU countries from 1999 to 2004 through regression models. They showed that different types of banks had different performance (private-owned banks had better returns than mutual and government-owned banks) and that different types of risks had different impacts on different types of banks (e.g. mutual banks had better credit risk management efficiency than private and public sector banks). Similarly, Chen (2020) also investigated the effects of different types of risk on performance. He analysed 43 Chinese banks from 2010 to 2014 and showed that credit risks impacted bank performance differently based on their types through the decomposition of the profit change model. Both studies suggested that different types of banks had different focus points when managing risks and that they should develop different operating strategies.

Finally, a few studies compared impact of risk on fintechs' performance with that of traditional banks. Khanboubi & Boulmakoul (2018) presented the importance of risk management in both fintechs and traditional banks and present the differences between these two types of banks (e.g. fintechs need to pay more attention to cybercrime and data security than traditional banks) . They suggested that both of these need to optimise risk management through big data management, and that traditional banks also need to set up new sectors, train staff and develop technological services. Through case studies in the UK and the US, Mohan (2018) suggested that banks and fintechs should work together towards faster innovation in the financial system. Where Jagtiani & Lemieux (2017) already proved traditional banks and fintechs were working together to provide better lending in the US by using regression models.

Therefore, based on the previous literature, we note some potential limitations and biases when selecting fintechs and challenger banks when analysing them against traditional banks. Firstly, most of fintechs and challenger banks are still unlisted (even the giants), which means not all of them publish their business reports for us to analyse. So, the bias could be that researchers could only analyse fintechs which publish reports. As time develops, the situation could be solved with more fintechs and challenger banks providing their reports to the public. Secondly, many fintechs and challenger banks have a large chance of failure. When a fintech fails and leaves the market, we have limited opportunities to find their data to analyse them and learn lessons. So, the bias here could be that researchers can only analyse relatively successful samples. Thirdly, the fintech industry is developing rapidly, and research might be outmoded. However, even with these limitations and biases, it is still worth investigating the fintech area. The research can still be part of the story, understanding the situation of the current industry and providing suggestions for managers and regulators who are interested in this area. As a new type of bank, the main risks they face during operating are still similar to traditional banks, thus, comparisons between them are worth investigating.

2.4 Conclusion and Research gaps

With the development of technology and increasing connections in the banking industry, fintechs have become established and are now a critical field of interest. Also, because of the 2007-09 financial crisis, risk management has become an essential field in researching banking industry. However, the performance of fintechs, especially their risk management and comparisons between traditional banks and fintechs, has been under review. The existing literature shown above demonstrated some pieces of evidence.

This chapter discussed some of the existing risk management performance, regulations related to risk management, and impacts of risks on the performance of traditional banks and challenger banks and fintechs. Since banks take many risks, they need to manage these risks. Through risk management, managers could use historical data, regulations and models to identify, analyse, monitor and control all these risks (Srivastav, 2013). Many studies (e.g. Valentine, 2012 and Freyer, 2013) presented the importance of risk management and showed what managers should do to improve governance in the bank. Some of them tried to provide solutions for risk management, mainly focused on traditional banks (e.g. Wu and Olson, 2010). However, in order to investigate better risk management in the banking industry, other types of banks (e.g. challenger banks and fintechs) are worth studying as well. This literature review concluded that, in general, a better reputation, optimum liquidity conditions and lower cost percentages in income would produce a better bank performance. Moreover, improving risk management efficiency is one of the most important ways to support better performance in banks. Moreover, we showed the important roles of China, the UK and Australia in the global banking and fintech industry. We also found many studies also interested in these three countries, which indicates their importance in studies in risk management. Thus, we can see that our countries of interest are indeed worth investigating and will provide a contribution to the area.

This review suggested that previous research on risk management provided some explanations about the relationship between risk management and bank performance for traditional banks. However, only a few of these studies explained this relationship for challenger banks and fintechs and provided only limited explanations. Besides this, no comparisons have been carried out regarding the relationship between risk management and bank performance for traditional banks and challenger banks and fintechs. Thus, this review revealed three research gaps, which are: (i) most of the research work on risk management has been done on traditional banks but not on challenger banks and fintechs. (ii) many studies mainly focused on one or two particular countries or types of risks that impact on bank performance; (iii) previous research also failed to provide comparisons between traditional banks and fintechs.

This research targets all three gaps. We note, however, that the second issue cannot fully be covered because it would involve a too large sample size, which is beyond the scope of this research. Thus, future research should focus on the remaining gaps. Thus, this research will address these limits in the risk management of fintechs and compare the results with traditional banks by applying a triangulated analysis between three countries (namely China, the UK and Australia).

CHAPTER THREE

RESEARCH DESIGN AND METHODOLOGY

3.1 Introduction

As an academic activity, research needs to define problems, test hypotheses, consider possible solutions, collect and analyse data, test collected data and then deliver research findings. Naslund (2002) said that logical research outcomes should be developed based on scientific principles through a well-defined research methodology. Kaplan (1983) indicated that a well-developed research methodology can provide a good understanding of the products and processes of scientific enquiry (Kuhn, 1962). Researchers now need to look for suitable or modified methods and techniques for observations, inference and analysis. Through the developing of methodology over the years, there are plenty of research methods that can be used in research, such as descriptive and analytical research, applied and fundamental research, quantitative and qualitative research. In all of these types, quantitative and qualitative are the two basic approaches. According to Kothari and Garg (2014), quantitative research measures the characteristics based on quantitative analysis, including mathematical and statistical explanations. On the other hand, qualitative research is concerned more about opinions and behaviour based on the research aim. Even though these approaches are not perfect, all these methods and techniques can be used to achieve results that successfully provide research findings.

Therefore, identifying an appropriate methodology for research questions is essential. While it has seemed that quantitative and qualitative methods are mutually exclusive, these two methods can be integrated. It is a methodology increasingly used by researchers across different disciplines. This argument is supported by many research methodologists (e.g. Cronholm & Hjalmarsson, 2011; Harrison, 2013; Teddlie & Tashakkori, 2008). They suggest that combining these two approaches could better answer research questions and provide more complete knowledge about research theory and practice.

This research adopts a combination of quantitative and qualitative methodology, which are the two main theoretical approaches to the research methodology. Based on the different research goals, this chapter will explain the reasons for adopting a mix-methods based approach. The simple explanation is because the purpose here is to use all means possible to understand the comparisons between bank types and countries. Building statistical models (the quantitive approach), will make use of available data, which has been collected and will be analysed through panel data regression models. Alongside this, the qualitative approach will consist of case studies in order to understand some of the detail behind the overarching differences found in the quantitative results. In this way, the aim is to get a clear understanding of traditional banks and fintechs.

The following subsections describe the research design, procedure and a summary of the sections. Section 3.2 will present philosophical and epistemological considerations. Then, Section 3.3 will show the procedure carried out together with the research process and timeline. Section 3.4 will present the research design, which includes countries, variables and case selection for both traditional banks and fintechs. Also, it will indicate the method and tool selection for statistical analysis. Finally, there will be a conclusion in Section 3.5.

3.2 Research Philosophy

The term research philosophy can be seen as the beliefs, assumptions and justification for knowledge development. It considers what knowledge has been developed in a particular area and is guided by research paradigms. Research paradigms are the historical view of knowledge which shows what the knowledge reality is, how researchers know about it, and how to find out more. Thus, paradigms provide ontology, epistemology, methodology, axiology and the notions of ethics (Saunders et al., 2009). Paradigms support the philosophy of the research, such as positivism, interpretivism and critical theorism. It also promotes the research approach (Guba, 1990).

In order to choose a suitable methodology for research, the basic premise needs to find out specific epistemology of research paradigms. Researchers, whether using a quantitative or a qualitative approach, display particular epistemological and ontological views about research reality and how the research should be conducted (Saunders et al., 2009). Prior to applying research results, it is imperative to select an epistemological stance that aligns with the beliefs of the researcher about the knowledge that will be constructed. If the researcher assumes the knowledge is objective and tangible, and that the researcher is just an observer of the knowledge, then this kind of researcher is called a positivist. On the other hand, if the research assumes the knowledge is subjective and personal, and that the researcher is involved with the knowledge, then this kind of researcher is called an interpretivist (Coghlan et al., 2004).

3.2.1. Critiques of quantitative, qualitative and mixed research methods

Positivism and interpretivism are based on different philosophical assumptions regarding both knowledge consideration and research approaches. Positivist epistemology aims to understand a subject by identifying and then explaining the phenomenon by components, and it constructs a relationship between components. Thus, positivist researchers usually prefer a more quantitative approach (Cavaye, 1996). On the other hand, interpretivist researchers who are already involved in the research, like the participants, tend to prefer a more qualitative approach.

Eid and Trueman (2004) said that quantitative research approaches are typically based on a logical structure that builds expectations about the links between the concepts in the hypotheses. Therefore, the determination of the specific links between concepts by the hypotheses would lead to acceptance or rejection of the result of a theoretical proposition. Thus, quantitative research approaches emphasise the research methodology, procedure and statistical models of validity on the research topic. The quantitative approach also relies on statistical measurement and the analysis of datasets to determine the relationships between concepts.

However, Bryman (1993) and Gable (1994) criticised the quantitative research approach. They pointed out some existed issues that traditional quantitative approach have, where Bryman (1993) focused more on the orderliness and occupations in using a quantitative approach, such as individualism, replication and generalisation, Gable (1994) paid more attention to the subjects' relationships and providing descriptive statistics and analysis in using a quantitative approach. Also, Gable (1994) considered weaknesses of the traditional quantitative survey research, including limited sample sizes and misinterpretations by respondents of the survey.

On the other hand, with regard to the qualitative approach, Marshall and Rossman (1989) provided a rationale for qualitative research which was mainly about the influence of human behaviour and how to analyse it to understand social behaviour. Thus, qualitative researchers consider the meaning of the phenomenon with descriptions. The weaknesses of the qualitative approach are also determined by its nature. Firstly, data collection is more time-consuming as more types of data need to be collected. Secondly, the relationship between research and theory can be weak, as the investigated issues may only be linked to broader theoretical issues. Finally, external validity is limited, as qualitative research is trying to solve a particular research question, rather than a generalised one (Marshall & Rossman, 1989). However, qualitative analysis can also be representative for the field of study and then present answers to generalised questions in this field (Flick, Kardorff & Steinke, 2004).

Furthermore, researchers can be both positivist and interpretivist (combining the quantitative and qualitative approaches), which is called mixed methodology or methods. Gummesson (2000) pointed out that since the late nineteenth century, social scientists have begun to merge the positivist and interpretivist paradigms. The trend of combining both philosophical stances could build a bridge between the two extreme viewpoints. Easterby-Smith et al. (2002) called the mixed methodology triangulation, and they classified triangulation into four different types. The first one is data triangulation which represents data collected from different sources and/or different times. The second one is investigator triangulation, which represents the situation where different investigators collect data separately and independently. The third one is methodological triangulation, which represents the situation where quantitative and qualitative approaches are both employed. The last one is called triangulation of theories, which is when the researcher uses theory in one discipline to explain a phenomenon in another discipline.

3.2.2. Justification for the research methodology

In the aforementioned three types of research methods, the third type (mixed methodology) is believed to be suitable for this research. Easterby-Smith et al. (2002) note that mixed research methods provided more significant empirical results and support for the research question. Based on Easterby-Smith et al. (2002), a triangulation methodology will be applied in this research to study risk management and its influence in banks' and fintechs' performance in China, the UK and Australia. The output of the research will be, firstly, from an academic perspective, to apply and improve methodology (how to manage risks through panel data regression models) for both traditional banks and fintechs in the future. Secondly, from a practice perspective, the research will provide insights and benefits in risk management for traditional banks and fintechs. Furthermore, from a philosophical perspective, this research will view the issues under investigation from both the positivist and interpretivist perspectives, rather than either extreme viewpoint.

Even though this research mainly uses a quantitative approach, a qualitative approach (i.e. case studies) will be used to assist in completing the research. This research pulls together relevant theories and statistical models with the primary data (both quantitative and qualitative) to support the analysis of this research area.

3.3 Research Procedure

Based on the aims of this research, reviewing the literature is the first applicable method in this research. Literature could offer terminology, articles on risk management, bank performance, fintechs developments, and statistical models used in the banking industry. The background and theory of the research will be known well, and similar research methods and data analysis methods will be adequately understood. Besides this, the limitations of previous studies can be detected with these comparisons. These limitations can be considered and avoided through the investigations in this research. Besides the literature review, the primary method will be empirical research. The simplest explanation of empirical research is using empirical evidence to answer the research questions. The ways to gain empirical evidence can be through observation and experience, and to analyse the empirical evidence using quantitative or qualitative approaches. The aim of using this is to discover and interpret the link between theories and facts. This methodology will be helpful to investigate the validity of the hypothesis and make the research more valuable in the area (Kauffman & Tallon, 2009). Therefore, this research adopts the empirical research and uses a quantitative analysis combined with a qualitative analysis. This approach suits the research purpose, which enables us to develop panel data regression models to test the relationship between risks and bank performance by observing the banks' reports. Also, it will enhance the context of the fintechs' development and operation in recent years. Thus, based on previous studies and the mixed methodology this research adopts, we can use Figure 3.1 to describe the research procedure.

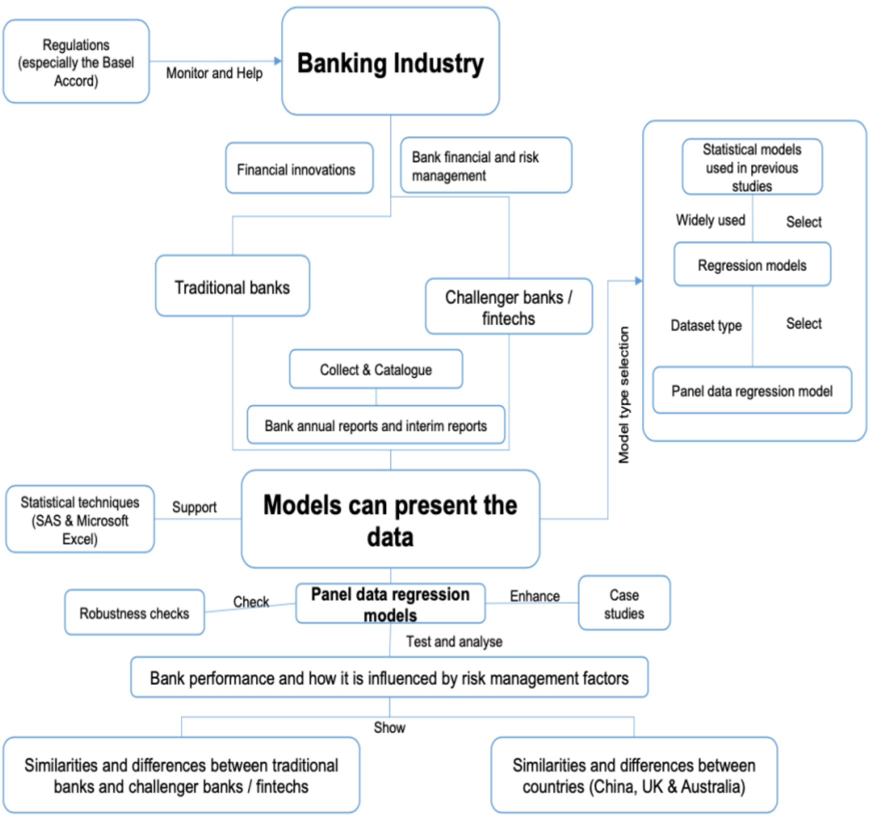


Figure 3.1 The flow of the research procedure

3.4 Research Design

To specify the research aim and objectives, the research design is to set different procedures which are like a framework for the whole research study. It defines the research type, data collection methods and statistical analysis approaches (Creswell, 2009). The following subsections present the specific research design. Section 3.4.1 explains the data gathering strategy. Country and bank selections are presented in Section 3.4.2. Section 3.4.3 justifies their choice and lists the specific selections made for our case studies. Section 3.4.4 discusses the source of the data and the specific variables selected. Section 3.4.5 presents the choice of analytical models that will be used to scrutinise the data. Finally, the analysis tools are outlined.

3.4.1 Data gathering strategy

Before venturing into data gathering, we conducted a brainstorm to help evaluate and prioritise the best solutions for the research implementation. The concept of this brainstorm was to consider ideas around the research objectives and look at them critically, to ensure that in samples and variables selection are unbiased and useful information is gathered. Our ideas about data sources are based on previous studies and conventional methods in bank-related research. As annual and interim reports are easy to obtain, they are the primary source for regulators and investors to look for information on bank performance and bank risk management situations. Therefore, these two report types were chosen as the data source to use with official bank publications. Thus, data source could be seen reliable, together with proved by previous literature with samples and variables selection, with this choice, the quality of data is guaranteed (Crooks, 2015).

Based on Miles et al. (2014), detailed and particular features in the bank financial reports can be selected to answer the particular aims specified in this study. This choice will, therefore, enable exploration and understanding of the themes in our research objectives and help us to achieve them.

3.4.2 Country and bank selections

The research domain can be defined as different types of banks in different countries. The representative banks will be selected from traditional banks and fintechs in China, the UK and Australia. The main reasons for choosing these countries are:

- The UK is the global centre of fintechs and the global leader in banks and challenger banks.
- China has had significant developments in challenger banks and fintechs, and it has become an essential country in the worldwide banking system.
- Australia has a unique position in the global financial system with its location. Its financial system operates mainly based on the Western model (like the UK), but its performance is relatively better than western countries. The typical example is the last financial crisis. Australia suffered fewer impacts than other developed countries. This is not only because of its different global location but also due to its collaborations with China.
- As measured by GDP per capita, the sample countries include both developed countries (the UK and Australia) and developing countries (China). These results are relatively comprehensive by investigating all three countries. Comparing the differences that exist between these countries could together raise awareness of the differences between developed and developing countries' banking risk management.
- All three countries are interconnected through the fintech industry. For example, many Chinese investors invest in the fintech industry in the UK and Australia, which can help investors to gain experience and management skills in operating with fintechs and banks. Moreover, successful Chinese fintech unicorns can also provide experiences for other countries as a reference.
- Through analysing three countries, the results are relatively comprehensive with triangulated comparisons rather than paired comparisons.

- The research is being undertaken in the UK, and therefore this further justifies the UK being an appropriate choice.
- The research is being undertaken by a Chinese national, and so this both provides some specific national background and adds some personal interest to the outcome.
- There are fewer fintechs founded in developing countries than in developed countries, which means that there are fewer options to select for investigations.
- The study must be limited in size and scope because of the limitations on time and resources so that considering more countries is not practical.
- In addition, as the most influential country in the world economy, the US's fintech area is also one of the top countries in the world. It could have been selected for comparisons in this research. However, the main reason we did not select the US as one of our investigating countries is because of the developing of the Chinese economy. As China's economy develops, the relations between China and the US are becoming tense. Although the collaboration continues, in many areas, competitive relations are more obvious than cooperation. In the area of fintech, the cooperation between China and Australia was closer during our investigated time period. Thus, instead of the US, Australia was selected as the third country in this research.

Regarding our bank selections, a few large banks characterise the banking industry with a dominant share of business and markets, and various new small banks hold the rest of the industry. Although, as discussed in Chapter 2, there are limitations that existed in selecting fintechs and challenger banks as a comparative group. They are still worth comparing with traditional banks based on the development of fintech and the growing interests of the market and government. Given the time constraints and availability of the fintechs' data, 11 challenger banks/fintechs were decided to be the sample size for each country. The main reason for selecting 11 fintechs is that most of the fintechs had not joined the share market or were established recently. Many fintechs, even some famous fintechs, do not publicly provide their financial and management reports.

Although there are more traditional banks which provide enough data to analyse, in order to compare between traditional banks and challenger banks/fintechs, eleven traditional banks were also selected to be the sample size for each country. Although unequal sample size still could apply comparisons, in order to have an equal comparison between these two types of banks together with time-consuming for more sample collections, the equal sample size could be a more appropriate choice in this research.

Table 3.1 shows all the selected traditional banks and fintechs in this study. There are eleven traditional banks selected in each country and these have large assets and a relatively long history. The criterion for traditional banks' selection is that these banks originated in the selected country are, supervised by the local financial regulatory authority and are in the list of the top 20 banks in terms of market capitalisation or estimated market capitalisation in 2017. For example, Bank of China (BOC), Industrial and Commercial Bank of China (ICBC), Agricultural Bank of China (ABC), China Construction Bank (CCB) and Bank of Communications (BOCOM) were selected as Chinese traditional banks. These five traditional banks were the so-called 'big five' of Chinese banks and held almost 35% of assets in the Chinese banking industry (Men, 2018). For the UK, we selected HSBC, Royal Bank of Scotland (RBS), Lloyds Group, Standard Chartered and Barclays, which are also the five largest UK banks (Misach, 2018). For Australia, we followed the same selection process. The 'big four' Australian banks were selected, which are: Commonwealth Bank of Australia (CBA), Westpac Banking Corporation (Westpac), Australia and New Zealand Banking Group (ANZ) and National Australia Bank (NAB) (Australian Prudential Regulation Authority (APRA), 2018).

On the other hand, the critera for selection of the fintechs were that they were originated in the selected country, operated bank-related business, publish financial reports, are supervised by the local financial regulatory authority and are in the list of top 50 challenger banks/fintechs in terms of market capitalisation or estimated market capitalisation in 2017. For example, YiRenDai was selected as a Chinese fintechs. It was a fintech unicorn in China and was the first Chinese fintech IPO that joined the

New York Stock Exchange (NYSE) in 2015 (CreditEase, 2016; Men, 2018). For the UK, Atom was selected, which was the first fully mobile challenger bank which had a bank licence in the UK (Atom bank, 2014). For Australia, following the same selection process, Tyro was selected because it was the first fintech bank which obtained the Australia acquirer bank licence in 2005 (Tyro, 2016).

	Traditional banks	Founding year	Challenger banks/ fintechs	Founding year
China	Industrial and Commercial Bank of China (ICBC)	1984	YiRenDai (YRD)	2012
	Bank of China (BOC)	1912	Huifutianxia (HF)	2013
	China Construction Bank (CCB)	1954	Qudian (QD)	2014
	Agricultural Bank of China (ABC)	1951	Zhejiang e-commerce bank (Mybank)	2015
	Bank of Communications (BOCOM)	1908	Webank (WB)	2014
	China Minsheng Banks (CMBC)	1996	Ideacome (IC)	2012
	China Merchants Bank (CMB)	1987	JD finance (JD)	2013
	China Citic Bank (Citic)	1987	Rong360 (R360)	2011
	Shanghai Pudong Development Bank (SPDB)	1992	Lufax (LF)	2012
	Industrial Bank (IB)	1988	Tianjin Jincheng bank (KCBE)	2015
	China Everbright Bank (CEB)	1992	PaiPaidai (PPD)	2007
UK	Lloyds Group	1765	Shawbrook Bank	2011
	HSBC	1866	Aldermore Bank	2009
	Barclays	1690	Atom Bank	2014
	Standard Chartered	1969	Monzo Bank	2015
	Royal Bank of Scotland (RBS)	1727	Metro Bank	2010
	NatWest	1968	Clear Bank	2014

	Nationwide Building Society	1846	Gatehouse Bank	2008
	Clydesdale	1838	Starling Bank	2014
	Virgin Money	2003	Revolut	2015
	Yorkshire Building Society	1864	British business Bank	2014
	Coventry Building Society	1884	Cambridge & Counties Bank	2012
Australia	Commonwealth Bank of Australia (CBA)	1911	Ondeck	2006
	Australia & New Zealand Banking Group (ANZ)	1835	Zipmoney	2013
	National Australia Bank (NAB)	1858	Afterpay Touch	2014
	Westpac Banking Corporation (Westpac)	1817	Xero	2006
	Bendigo and Adelaide Bank (BA bank)	1858	Novatii Group	2016
	Bank of Queensland (BOQ)	1874	Pushpay	2011
	Macquarie Bank	1969	Tyro	2003
	AMP Bank	1988	Change Financial	2011
	Suncorp Bank	1902	ManagedAccounts	2004
	Heritage Bank	1875	Mint Payments	2007
	IMB Bank	1880	Wisr	2015

Table 3.1 Sample selections (traditional banks and fintechs)

Now that the banks and fintechs had been selected, it is necessary to consider the appropriate time period to study. The period 2013-2017 was chosen because this time period shows the performance of all of these banks after the recent financial crisis. In addition, many of the fintechs did not exist prior to the recent financial crisis. Some of them were founded during or after the financial crisis. They were in their infancy and such fintechs were often not willing to present their annual or interim report for the public to see. Also, combined with the differences that exist in the start-up and reporting periods of fintechs between the chosen countries, the year beginning 2013 provides a comparable starting point. Even though reports could be found from 2010 for fintechs in the UK and Australia, for Chinese fintechs, they were not available until 2013. For traditional banks, of course, they all have a long history, but as the aim to compare the different types of bank, the selection needs to follow the fintechs.

Moreover, following the regulations, traditional banks and fintechs all publish their interim reports and annual report. Thus, the time period is selected from the second half from 2013 to the second half of 2017. How these traditional banks and fintechs have managed their risks and improved their performance since 2013 can be investigated, and the differences between them can be compared.

3.4.3 Case studies

Yin (2018) defined the case study as an empirical research method that investigates a contemporary phenomenon in-depth and in a real-life context. Thus, through case studies, particular understanding and insights can be gained. Thus, the potential use of case studies includes: first, the phenomenon can be learned about. Moreover, from actual practice, the relevant theory is verified. Secondly, a relatively full understanding of the nature and complexity of the phenomenon can be seen (Farquhar, 2013).

Case studies investigate the scope of the research area in a small number of units, and this small number of cases contrasts with a large number of sample features. It can then answer the research questions in a controlled way. Moreover, case studies can also concern the phenomenon in context. Thus, we can look into what happens in the actual situation. For business researchers, many advantages exist in looking into a particular location, company or industry. However, case studies have limitations. One of the main limitations is that findings from a small number of cases cannot extend to a more general situation where the quantitative survey research applies (Farquhar, 2013).

Thus, as this research will adopt the mixed methodology, case studies as a qualitative approach will be provided to support the findings from the panel data regression models in the quantitative approach. Based on Table 3.1, cases are selected from the whole sample. The selected examples are listed in Table 3.2. As there are two types of banks included in the whole sample, the selection process followed the pair matching method.

Firstly, for traditional banks, the cases studied here are the largest bank in each country, and they survived through the 2007-09 financial crisis. Secondly, for fintechs, the cases studies here are the most famous unicorn fintechs which received licenses earliest and their size is well-developed in each country. Thus, one bank in each type from the three countries is chosen, resulting in a total of six cases.

Country	Traditional banks	Challenger banks/fintechs
China	ICBC	YRD
UK	HSBC	Atom
Australia	ANZ	Tyro

Table 3. 2 Case studies samples

In more detail, because of the importance of risk management in the banking industry, some banks performed outstandingly, while some banks had difficulties. In order to illustrate the risk management and risks' influence and inform this research's objective, risk management of the cases is worthwhile to investigate. Therefore, a similar approach to case studies is borrowed from Docherty and Viort (2014). We set out six case studies in both traditional banks and challenger banks and fintechs. These cases will contain lessons learned from risk management, or risk mismanagement, and their impact on performance. These cases are not only case studies of the individual banks and fintechs, but also provide an insight into the structural issues of the banking industry with respect to both traditional banks and fintechs.

3.4.4 Data collection and extraction

After deciding on our sample, the next step is to collect related variables for further analysis. We hand-picked these variables from bank annual and interim reports. In Chapter 2, the literature review, we reviewed some possible variables used in analysing bank risk management and their impacts on bank performance. Based on our literature review, Table 3.3 and Table 3.4 identify the dependent and independent variables with their meanings and expected effects with respects to dependent variables which are involved in this research with the panel data regression models. Moreover, in order to compare three countries using one standard, as the most influential international settlement currency, except for the percentage, variable (VaR) is collected based on millions US$ and variable (EPS) is collected based on US$ per share.

Dependent variables (Bank performance variables)	
Variable	**Meaning and measure**
Return on Asset **(ROA)**	ROA is an indicator used to measure the ratio of the bank's profit to the average assets of the bank. It reflects the comprehensive utilisation of assets. $$ROA = \frac{Net\ Income}{Total\ Asset} \times 100\%$$
Return on Equity **(ROE)**	ROE is an indicator that shows the return on investment of shareholders. It reflects the bank's ability to use net asset value to generate a net profit. $$ROE = \frac{Net\ Income}{Total\ Equity} \times 100\%$$
Earnings per Share **(EPS)**	EPS is a profit indicator for banks in the share market. EPS and the bank's stock price are linked, so it is one of the critical elements that the banks' existing shareholders and potential investors use to measure the bank. $$EPS = \frac{Profit - Preferred\ Dividends}{Weighted\ Average\ Common\ Shares}$$

Table 3.3 Dependent variables and their definitions

Independent variables (Bank risk variables & size)		
Credit risk variable	**Meaning and measure**	**Expected effect**
Non-performing Loan Ratio **(NPL)**	The lender of the loan believes the borrower will not make the payments 90 days after the due date, which makes the loan become a non-performing loan. $$NPL\ Ratio = \frac{Non-performing\ loan}{Total\ loan} \times 100\%$$	Negative
Net Charge-off Rate **(NCO)**	A net write-off is a debt owed to the bank that is unlikely to be recovered. This 'bad debt' is usually written off as total write-offs. Non-performing loans may be charged off as bad debt on a quarterly or half-yearly basis. $$NCO\ Ratio = \frac{Net\ Charge-off}{Average\ Outstanding\ loans} \times 100\%$$	Negative

Total Loan Loss Ratio **(LoanR)**	Every loan loss of the bank during the financial period, including impairment, loss and write-off loans. The LoanR is representative of the status of total credit security. $$LoanR = \frac{\text{Total loan loss}}{\text{Total loan}} \times 100\%$$	Negative
Market risk variable	**Meaning and measure**	**Expected effect**
Value at Risk **(VaR)**	The definition of VAR is 'Given some confidence level α in (0,1), the VaR of the portfolio at the confidence level α is given by the smallest number l such that the probability that the loss L exceeds l is not larger than (1 – α)'. So the equation shows $VaR\alpha = inf\{l \in \Re: P(L > l) \leq 1 - \alpha\} = inf\ \{l \in \Re: FL(l) \geq \alpha\}$' (Frey & McNeil, 2002). The left is the definition of VaR. The equation on the right assumes a potential probability distribution, which makes it valid only for the parameter VaR Following the regulators requirements, banks publish their VaR in annual and interim reports at 99% in180-days. In addition, the VaR can also be found in Bloomberg.	Positive or Negative
Liquidity and capital risk variable	**Meaning and measure**	**Expected effect**
Liquidity Coverage Ratio **(LCR)**	LCR shows highly liquid assets held by banks to meet short-term obligations, and Basel III asks banks to obtained at least 100% (since 2015). LCR ensures that financial institutions have the necessary assets to survive any short-term liquidity disruption. $$LCR = \frac{Stock\ of\ High\text{−}Quality\ \ Liquidity\ Asset}{Excepted\ Total\ net\ cash\ outflows\ over\ the\ stress\ period} \geq 100\%$$	Positive
Current Ratio **(CR)**	CR is a measure of the liquidity and efficiency ratio of a bank's ability to repay short-term liabilities with current assets. $$CR = \frac{Current\ Assets}{Current\ Liabilities} \times 100\%$$	Positive
Tier 1 Capital Ratio **(T1)**	T1 ratio is the ratio of a bank's core equity capital to its total risk-weighted assets. Basel III aims for a minimum of T1 ratio of 6%. $$T1\ Ratio = \frac{Tier\ 1\ Capital}{Risk\ Weighted\ Assets} \times 100\%$$	Positive

Debt-to-Asset ratio **(D/A)**	D/A evaluates a bank's debt levels. D/A indicates the financial health of a bank and how over-extended they may be. $$D/A\ Ratio = \frac{Total\ Debt}{Total\ Assets} \times 100\%$$	Negative
Debt-to-Equity ratio **(D/E)**	D/E ratio is an indicator to measure the relationship between creditors' contributions and the owners' contributions. It also shows how far shareholders' equity can meet a company's obligations to creditors in a liquidation. $$D/E\ Ratio = \frac{Total\ Debt}{Total\ Equity} \times 100\%$$	Negative
Reputational risk variable	**Meaning and measure**	**Expected effect**
Brand Value Change **(BVC)**	The percentage change in the bank's brand value in each year and half year basis. $$BVC = \frac{Change\ of\ Brand\ value_{t(n)-t(n-1)}}{Brand\ value_{t(n-1)}} \times 100\%$$	Positive
Operational risk variable	**Meaning and measure**	**Expected effect**
Operational risk exposure **(ORE)**	In Basel II, one of the approaches to calculating the operational exposure is called the standardised approach (operational risk) where the standard indicator is 15% of gross income for the commercial banks (Basel Committee on Banking Supervision, 2014).	N/A
Operational risk percentage **(ORP)**	The operational risk events represent the already occurred and reported operational risks with money lost. ORP shows the rate of operational risk loss in banks' operational risk preparations. If the ratio is less than 15%, it indicates the preparation is sufficient. If the ratio greater than 15%, it suggests the preparation is not enough, which may cause an operational risk disaster for the bank. $$ORP = \frac{Known\ Operational\ Risk\ Loss}{Gross\ Income} \leq 15\%$$	Negative
Cost-to-Income Ratio **(C/I)**	C/I shows how efficiently the bank is being run. The lower the ratio, the higher profits the bank earns and this indicates that the bank in performing better in its operations. $$Cost/Income\ Ratio = \frac{Operational\ cost}{Operational\ income} \times 100\%$$	Negative

General Information	Meaning and measure	Expected effect
Bank Size	Log of the bank's total asset $Size = ln(Asset)$	Positive or Negative

Table 3.4 Independent variables, their definitions and expected effects

For the variables mentioned above, some of them were found in the secondary database (e.g. Bloomberg) for listed banks, such as ROA, ROE, EPS, NPL, VaR LCR, CR, D/A, D/E, T1, Asset and C/I. However, other variables (e.g. NCO, LoanR, ORE, and ORP) needed to be collected or calculated from the banks' annual and interim reports. Moreover, for the banks that are not part of the share market, all variables must be collected from the annual and interim reports. In addition, as there are more missing values for China's data on Bloomberg, we used another secondary database called the China Stock Market & Accounting Research Database (CSMAR) which provides data particularly for China's listed companies to collect variables. Similarly, it provides ROA, ROE, EPS, NPL, VaR, LCR, CR, D/A, D/E, T1, Asset, and C/I. Furthermore, NCO, LoanR, ORE and ORP were obtained from banks' annual and interim reports. Table 3.5 outlines the sources we used for data collection for each country and each bank type.

	Traditional banks	Challenger banks/fintechs
China	CSMAR and bank reports	CSMAR, Bloomberg and bank reports
UK	Bloomberg and bank reports	Bloomberg and bank reports
Australia	Bloomberg and bank reports	Bloomberg and bank reports

Table 3.5 Data source for each country and bank type

3.4.4.1. Dependent variables

ROA, ROE and EPS are selected to represent the bank performance as dependent variables. Through continuous development, ROE and ROA have become the commonly used factors in banks. The use of ratio analysis to evaluate bank performance and measure bank profitability is now well established. Both ROE and ROA have been used for a long time to represent bank performance in assets or equity. These show the percentage of the income of bank assets or equity in a financial year. Therefore, banks can compare their current and historical performance in investments and earnings (MacDonld & Koch, 2006). Similar to Bailey et al. (2011), Erdogan (2016) and Rauf & Ismatullaevich (2013), this research uses both ROA and ROE as dependent variables. Following Abubakar et al. (2016) and Siddik, Kabiraj & Joghee (2017), EPS is also used as another dependent variable. EPS is also a common factor in measuring bank performance in the stock market. It is seen as the most critical variable in determining the stock price, which leads to its impact on the performance and profitability of banks in the stock market (Islam et al., 2014). Even though some of the fintechs are not on the stock market yet, the differences in the performance of traditional banks and fintechs are still worth monitoring and analysing. The main reason for this is that fintechs do tend to join the stock market.

3.4.4.2. Independent variables

For independent variables, variables are catalogued into six parts based on five bank risk types and bank size. The first risk type is credit risk. As stated in the literature review, credit risk is an essential type of risk that every financial institution is expected to reduce. Three relevant variables (NPL, NCO and LoanR) are collected. Following Carbo-Valverde (2016), Geng et al. (2016) and Zhang et al. (2011), we choose NPL and LoanR as representative variables in the regression models. The NPL is a favourable and widely used ratio used for analysing credit risk and represents the quality of a bank's assets. A higher NPL exposes banks to more credit risk. LoanR represents the status of a bank's financial security. When it becomes too high, the quality of loans collapses, and the value of the bank's assets drop as bad loans increase. Supported by Barth et al. (2018), the NCO is selected because it can help managers predict how much money will need to be written-off in the future. A higher rate means more loss which has to written-off in the credit asset. As said above, based on the literature, we expect that there will be a negative relationship between credit risk variables and bank performance.

The second type of risk is market risk. Similar to Kerkhof et al. (2010), value at risk (VaR) is chosen to represent the market risk variable. It is a widely used measure that shows the potential loss for the investments. It provides under normal market volatility and probability, the largest potential loss to a bank's portfolio in a future time (Frey & McNeil, 2002). Some the researchers argue that VaR has a negative impact on bank performance due to the fact that the higher values indicate higher market risk (e.g. Kerkhof et al., 2010). However, William (2016) found that higher VaR did not reduce bank performance. As both negative and positive influence are shown in previous literature, we do not have any prior expectation for the variable with respect to its effect on bank performance.

The next risk type is liquidity and capital risk. Following Jin et al. (2011), Kiema & Jokivuolle (2014), Zhang (2011) and combining requirements of financial regulations, five relevant variables (e.g. LCR, CR, T1, D/A and D/E) have been selected. We removed CAR and QR from the panel data regression models. This is because the CAR value contains T1 and T1 is of more concern to banks and investors in practice, and the CR value contains QR, where CR could show more of an overall result. As noted in the literature review and Table 3.4, LCR ensures that financial institutions have the necessary assets to survive any short-term liquidity disruptions. CR shows the bank's ability to repay current liabilities with its current assets. T1 shows the bank's financial strength in its capital. Thus, we expect that these three variables could have a positive influence on bank performance in our models.

D/A and D/E provide the debt level in the bank's asset and equity respectively, which we excepted to reduce bank performance. Thus, based on previous findings (e.g. Pinto & Joseph, 2017; Siddik, Kabiraj & Joghee, 2017), a negative relationship between D/A and D/E to bank performance are expected and this is that shown in Table 3.4. Moreover, the reason for choosing two debt-level variables is D/E demonstrates more directly that if the equity is negative, the banks perform poorly. On the other hand, D/A cannot prove that because the total assets are always positive. Thus, all variables selected in capital and liquidity risk represent a different angle which will provide a comprehensive view of banks' management of this type of risk.

Regarding reputational risk, similar to Cheung et al. (2011), we also use the percentage change in the bank's brand value as a representative factor to put into the models. We expect that it will positively influence bank performance. The fifth type of risk is operational risk. Since operational risk is difficult to manage and monitor, the Basel Accords require banks to prepare 15% of their gross income to react when operational risks occur (BCBS, 2015). This research follows the Basel Accords, and it calculates the cost of known risk events over the gross income as the ORP in the regression models. Compared with the required 15%, the higher the ratio, the worse the operational risk has been managed. If the ratio exceeds 15%, it indicates that terrible risks occurred and that the bank should pay much more attention to these to prevent this operational risk from happening again. Thus, a negative influence could be expected to be shown in models on bank performance. Similar to Diallo et al. (2015), the C/I is also selected for operational risk to put into the regression models. It shows the efficiency of operations management, including operational risk management. Although this ratio does not show specific operational risks, it shows the bank's overall operational efficiency. Changes in C/I can highlight potential problems. For example, if the ratio increases from one period to the next, it means higher operating costs for that bank. Thus, based on previous findings (e.g. Diallo et al. 2015; Shaban & James, 2018), we expect that C/I will negatively influence bank performance.

Finally, the bank's total asset is selected. Banks with different sizes may have various incentives to participate in investment and corporations. In panel data regression models, because the value of total assets is much bigger than other variables, the natural logarithm of total assets is used to represent the bank size in almost all literature. Thus, this research will follow them and use ln(asset). Some studies (e.g. Elsas et al., 2010; Tan, 2016) suggest that larger banks may have lower bank performance. Some the studies (e.g. Athanasoglou et al., 2008; Berger & Humphrey, 1994) suggest that larger banks can increase their performance to a certain level and after that their larger size will decrease their performance. Thus, there is no prior expectation for the effect of this variable on bank performance - both positive and negative could be shown for our dataset.

3.4.4.3 Dummy variables

Besides bank size, many previous studies added dummy variables to show the impact of bank ownership on bank performance for the traditional banks. For example, Fu & Heffernan (2009) and Tan (2016) tested if state-owned banks had better performance in China. In order to capture the relationship between bank ownership and performance, we follow the previous literature's suggestion in using a dummy variable for bank ownership (e.g. state-owned banks). However, Tan (2016) showed a positive relationship between State-Owned banks (SOB) and bank performance, whereas Fu & Heffernan (2009) argued for a negative relationship between them. Thus, we have no prior expectation for the effect of this variable on bank performance.

Based on the government explanations, in our sample, the 'big five' in Chinese banks are the state-owned banks. With regards to the UK, there are no state-owned banks. In more detail, because of the 2007-09 financial crisis, Lloyds bank group and RBS faced colossal losses, and the UK government bailed them out. Although the UK government owns a controlling stake of 43% of Lloyds bank group's and 73% of RBS' ordinary shares, the banks remained independent of government (BBC News, 2009). With regards to Australia, there are also no state-owned banks. In more detail, the CBA used to be the only state-owned bank in Australia. However, the CBA went privatisation in 1991 and became independent of government (CBA, 2019). Therefore, as only China has state-owned banks in our sample, the dummy variable will not be included in the analysis of Chapter 4. However, in order to have a comprehensive analysis, the Chinese traditional banks' results with the dummy variable will be shown in Appendix 1 and 2.

Dummy variable	**Meaning and measure**	**Expected effect**
Bank Ownership	Dummy variable equal to one for state-owned banks **(SOB)** and zero for other traditional banks.	Positive or Negative

Table 3.6 Dummy variable and expected effect

3.4.5 Research models selection

Regression analysis is a widely used statistical process for estimating the relationships between variables. There are two main purposes of regression analysis: (i) prediction and forecasting; (ii) to test the causal relationships between dependent and independent variables. For this research, as a part of the mixed methodology, panel data regression models will be built and analysed to achieve the research aims.

Before the analysis of any relationships, data need to be collected. Cross-sectional data, time-series data and panel data are three main types of data in research. The main difference between them is the entity and time period. Cross-sectional data contains data for multiple entities over a single time period. Time-series data contains data for single entities over multiple time periods. Panel data contains data for multiple entities with each entity observed over serval time periods (Watson, 2015). For this research, the variables listed above were hand-picked from annual and interim reports and were catalogued by country and type of bank into different Excel tables. The data are presented with the same variables in different years with different banks and countries repeatedly. Thus, the dataset in this research can be seen as panel data. As mentioned in the literature review, many studies have used panel data regression models to analyse bank performance and its influencing factors. This research will follow the previous literature, applying panel data regression models to analyse the collected data, test bank performance, and examine how different types of risks influence the performance.

There are several reasons why panel data analysis is of interest. Firstly, panel data analysis offers a solution to the problem of omitted variable bias caused by unobserved heterogeneity between entities, which is a common problem when fitting a model in cross-sectional data sets. Secondly, it can exploit the dynamics that cross-sectional data find hard to detect. Cross-sectional data usually consist of no more than a single year, but panel data analysis can avoid the problem of a limited time interval. The third attraction of the panel data analysis is that it often has a large number of observations. For examples, if there are n units of observation and these are undertaken in T time periods then there are potentially n*T observations each consisting of a time series of length T on n units.

The standard form of the panel data regression model is

$$y_{it} = \beta_0 + \sum_{j=1}^{k} \beta_j x_{it} + u_{it}$$

where y represent the dependent variable; x represents the independent variables; β_0 represents the constant term; $\beta_j\,(j = 1, \dots, k)$ are coefficients to be estimated; i and t are indices for the sections and time, respectively; $u_{it} = \alpha_i + \varepsilon_{it}$, where α_i is the individual-specific unobserved effect. For the fixed-effects approach, it includes δt, which is a trend term in t, which allows intercepts to shift over time. It allows α_i to be correlated with the regressor matrix x_{it} which means the fixed-effects assume that induvial-specific effect is correlated with the independent variables. For the random-effects approach, it shows an unobserved time-invariant and group-specific effect and assumes α_i is independent for all t in the random-effects. ε_{it} is the error term.

There are two main approaches in panel data regression models, namely fixed-effects models and random-effects models. In the fixed-effects models, there are three versions of estimations under this approach called within-groups fixed-effects, first differences fixed-effects, and least squares dummy variable fixed-effects. For within-groups fixed effects, the mean value of the variables on a given individual is calculated and subtracted from the data for that individual. When put into the general form of the regression model, it becomes $\bar{y}_i = \beta_0 + \sum_{j=1}^{k} \beta_j \bar{x}_{ij} + \bar{u}_{it}$ where $\bar{u}_{it} = \delta\bar{t} + \alpha_i + \bar{\varepsilon}_{it}$, then subtracting the mean variable equation from the general equation, gives $y_{it} - \bar{y}_i = \sum_{j=1}^{k} \beta_j (x_{jit} - \bar{x}_{ij}) + \delta(t - \bar{t}) + \varepsilon_{it} - \bar{\varepsilon}_{it}$, and as a result, α_i disappears. This version is called the within-group regression model, as it explains the variations about the mean of the dependent variable in terms of the variations about the means of the explanatory variables related to a given individual. For researchers, the major attraction of using this version is the possibility of tackling the unobserved heterogeneity bias. As noted above, this eliminates the fixed-effects (unobservable across-group differences) by expressing the values of the dependent and explanatory variables for each observation as deviations from respective mean values. Thus, to estimate the fixed-effects model with a large number of individuals, within-group fixed effects is adopted. For the within-group fixed-effect, SAS can apply a procedure called PROC Panel to analyse the dataset, which could do analyse fixed-effects analysis for fixed-individual or fixed-time with '/fixedone', or both with '/fixedtwo'. The procedure helps us analyse the dataset more clearly, such as, if we only need to fixed the individual-effect we can use fixedone.

In the second version, called first differences fixed-effects, a similar subtraction method is applied, but using the current time period minus the one previous time period from the observation. As the current model can be written as $y_{it} = \beta_0 + \sum_{j=1}^{k} \beta_j x_{jit} + \delta t + \alpha_i + \varepsilon_{it}$, the previous time period equation is $y_{it-1} = \beta_0 + \sum_{j=1}^{k} \beta_j x_{jit-1} + \delta(t-1) + \alpha_i + \varepsilon_{it-1}$, so differencing, the result becomes $\Delta y_{it} = \sum_{j=1}^{k} \beta_j \Delta x_{jit} + \Delta\delta + \varepsilon_{it} - \varepsilon_{it-1}$. Similarly, the equation show α_i and β_0 disappears. In the first two versions, the model is manipulated to eliminate the unobserved effect and leave the time effects. As moted above, this eliminates the unobservable effect of the parameters and causes the loss of the first time period for each cross-section ($t-1$ rather than t). Thus, to address the problem of omitted variables in a panel data analysis, first differences fixed-effects is adopted. For the first differences fixed-effect, SAS can apply a procedure panel to analyse the dataset with '/fdtwo printfixed BW'.

In the third version, called least squares dummy variable (LSDV) regression, the unobserved effect, α_i is brought explicitly into the model. For example, a dummy variable A_i can be introduced where it is equal to 1 in the case of an observation related to the individual i and 0 otherwise. The equation can be rewritten as $y_{it} = \sum_{j=1}^{k} \beta_j x_{jit} + \delta t + \sum_{i=1}^{n} \alpha_i A_i + \varepsilon_{it}$. Thus, the unobserved effect is treated as the coefficient of the individual-specific dummy variable, and $\alpha_i A_i$ represents a fixed-effect on the dependent variable y_i for the individual i (Dougherty, 2016). As noted above, this follows above-mentioned fixed-effects approach with adding dummy variables. For the LSDV fixed-effects, SAS can apply a procedure panel to analyse the dataset, which could do analysis with or without a dummy variable with '/w/o a dummy', or omits the intercept parameter from the model with '/noint' or place restractictions on the parameter estimates with 'restrict'.

As introduced in the previous paragraph about the fixed-effects approach, fixed-effects panel data regression models are not that efficient when the variables are constant for each individual. Fixed-effects models are better at showing the relationships between variables in a particular group, rather than the whole group representing an industry. One possible solution is random-effects models that can show relationships representing the whole industry. The random-effects regression model can be applied to panel data analysis. For the random-effects approach, the enquired equation is $y_{it} = \beta_0 + \sum_{j=1}^{k} \beta_j x_{jit} + u_{it}$, where $u_{it} = \alpha_i + \varepsilon_{it}$, α_i is the individual-specific unobserved effect which gives the unobserved time-invariant and group-specific effect, ε_{it} is the error term, and $E(u_{it}) = E(\alpha_{it} + \varepsilon_{it}) = E(\alpha_{it}) + E(\varepsilon_{it}) = 0$ by assuming individual unobserved heterogeneity is uncorrelated with the independent variables. (Dougherty, 2016). For random-effects, SAS can apply a procedure panel to analyse the dataset with '/ranone' or '/rantwo'.

Based on Greene (2008), Hsiao et al. (1999) and Torres-Reyna (2007), the fixed-effects models explore the relationship between predictors and outcome variables within sections and represents the whole group performance. In general, random-effects can be seen as efficiently with the assumptions underlying are believed to be satisfied (Hofmann & Werkhieser,2012), (Sheytanova,2004). In this research, panel data regression models are used to present the general performance of traditional banks' and fintechs' performance and how risks influence these performances, and not to present these specific banks' performance and their specific risk management. So, the random-effects models are more preferred to use. However, if there are omitted variables, the individual-specific effect α_i might be correlated with the independent variables in the random-effects model, so that the fixed-effects models is more robust.

Thus, we still need to run a test to determine which approach is preferred. The Durbin-

Wu-Hausman (DWH) test is a statistical hypothesis test widely used in econometrics. It is used to help researchers determine which approach should be used to analyse a panel dataset. The null hypothesis is that the random-effects is preferred to use. There is no correlation between the error term and the independent variables in the panel data regression model. In statistical terms, this implies that $Cov(\alpha_i, x_{it}) = 0$ for at least one i. The alternative hypothesis is that the fixed-effects model is appropriate. That is, a correlation between the error term and the independent variables in the panel data regression model exists and is statistically significant. In statistical terms, it states that $Cov(\alpha_i, x_{it}) \neq 0$ for all i. Then, a we choose a significance level. In general, this is where to be 0.05, which means if the test p-value is smaller than 5%, the researcher needs to reject the null hypothesis, and the fixed-effects model will be used in analysing data. If the p-value is larger than 5%, the researcher cannot reject the null hypothesis, and the random-effects models will be used in the data analysis. Furthermore, the Hausman statistic is calculated from the formula: $H = (\hat{\beta}^{RE} - \hat{\beta}^{FE})'[Var(\hat{\beta}^{RE}) - Var(\hat{\beta}^{FE})]^{-1}(\hat{\beta}^{RE} - \hat{\beta}^{FE})$, where $\hat{\beta}^{RE}$ and $\hat{\beta}^{FE}$ are the vectors of coefficient estimates for the random- and fixed-effects respectively. The Hausman statistic (H) is $\chi^2(k)$ distributed under the null hypothesis with the degrees of freedom k equal the number of factors. The observed H, it is compared with the critical values for the χ^2distribution on k degrees of freedom, and the null hypothesis is rejected if this is bigger than its critical value. If the test rejects the null hypothesis, then there is evidence suggest that the random-effects is biased and fixed-effects is the correct estimation procedure (Hausman, 1978; Sheytanova, 2004). For the DWH test, SAS can apply a procedure called PROC Model to determine model selection with '/hausman'.

Besides the Hausman test, we also need to test the stationarity of the dataset before running regression estimates. Stationarity is a critical concept in time series analysis and there are many studies on testing for unit roots in time series data. There are three main reasons for testing for stationarity: 1. Stationarity can strongly affect the behaviour and properties of the series; 2. The use of nonstationary variables may cause spurious regression problems. Spurious regression is a mathematical relationship in which two or more variables are not related to other variables, but, due to coincidence or the presence of another unseen factor, it may be incorrectly inferred that they are related.3. When the variables in a regression model are nonstationary, the standard assumptions of asymptotic analysis will be invalidated. In other words, the usual 't-ratio' does not follow the t-distribution and hypothesis testing regarding the regression parameters cannot be undertaken validly.

Moreover, stationarity needs to be considered when analysing panel data. For panel data models, the use of panel data unit root tests has become increasingly popular since the publication of the paper by Levin and Lin (1993). The main motivation for replacing the use of time-series unit root tests such as the Dickey-Fuller (DF) test, the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test with panel data unit root tests is that as the cross-sectional data increases, the power of the test increases. Another advantage of using a panel unit root test is that the test statistic is asymptotically normally distributed, whereas the time series unit root test follows an unconventional distribution, and the sample is usually approximately normally distributed in econometrics (Hadri, 2000).

The general equation used by the most panel unit root test is $\Delta y_{it} = \rho_i y_{i,t-1} + \sum_{l=1}^{p_i} \emptyset_{i,l} \Delta y_{i,t-l} + \alpha_i d_{it} + \varepsilon_{it}$, where d_{it} are the deterministic components. $\rho_i = 0$ suggests y has a unit root for individual i., while $\rho_i < 0$ suggests that the process is stationary around the deterministic part.

There are three main types of panel data unit root tests, namely the Levin-Lin (LL) test, the Im-Pesaran-Shin (IPS) test and the Fisher's (p_λ) test. Firstly, the LL test was developed by Levin and Lin (1992). They incorporated a time trend as well as individual and time-specific effects through the test model. In 1993, Levin and Lin updated their results of the panel unit root test and solved the problem of heteroscedasticity and autocorrelation. The major limitation of the LL test is that ρ is the same for all observations (H_0: $\rho_1 = \rho_2 = \cdots = \rho_N = \rho = 0$ and H_1: $\rho_1 = \rho_2 = \cdots = \rho_N = \rho < 0$), which leads to that null hypothesis not being resected under some circumstances when it should be, because the alternative is too strong to hold in some empirical cases.

Next, the IPS test relaxes the assumption that ρ for all i. is the same under the alternative hypothesis. Although the IPS test was designed as a generalisation of the LL tests, the IPS test assumes that T is the same for all cross-sectional units and that $E(t_{i,T})$ and $V(t_{i,T})$ are the same for all i. Thus, the IPS can only be applied to balanced panel data. There are many studies that have reviewed tests for significance of the results from N independent tests of a hypothesis like the IPS test, especially under meta-analysis. These procedures depend on different ways of combining the observed significance levels (p-values) from different tests.

At last, Fisher's (p_λ) test shows whether the test statistics are continuous, the significance levels are independent uniform (0,1) variables, and λ has χ^2 distribution with 2N degrees of freedom. The advantage of Fisher's test is that dataset need not be balanced as required in the IPS test and it can be carried out for any unit root test derived (Maddala & Wu, 1999).

Maddala & Wu (1999) compared these three models through Monte Carlo simulations and they concluded that Fisher's test (based on the ADF test) is the simplest and most straightforward to use and better than the LL and IPS tests. Moreover, their arguments also applied to tests using stationarity as the null, and to panel cointegration tests testing the null of no cointegration as well as testing the null of cointegration. In addition, for stationarity tests, SAS can apply procedure called PROC Panel to analyse the dataset with '/stationarity(fisher)'.

However, Maddala & Wu (1999) pointed out a major problem with panel data unit root and cointegration tests, which is an urge to generalise the tests used in univariate data to panel data under assumptions. This leads to more focus on technical details and less on the questions to be answered, making them less likely to be useful in practice. For example, for almost all tests, the hypothesis is either that all series are stationary/cointegrated or that all series are nonstationary/not cointegrated. This type of hypothesis lessens the value of the test. Moreover, by examining the same panel dataset using original regression, fully-modified regression and dynamic regression models, Azizi (2017) demonstrated that regression results were similar even when nonstationary variables were used.

Although there are issues that exist in the panel unit root test, many studies still run unit root before regression estimations. For example, Al-Wesabi & Yusof, (2020); Athanasoglou et al., (2008); Fainstein & Novikov, (2011); and Tan & Anchor, (2016) all run the unit root test before estimating the relationship between bank risks and performance. Thus, because this research complements the findings of the above mentioned studies and comparisons applied by Maddala & Wu (1999), we will also apply the panel unit root test (Fisher's test based on the ADF test) to test for stationarity in this research.

Heteroscedasticity also needs to be tested for when analysing regression models. One of the linear regression model assumptions is that the random error terms in the regression satisfies homoscedasticity. This means that they need to have the same variance. If this assumption is not satisfied, so that the random error terms have different variances, then the regression model has heteroscedasticity. Although OLS estimates are unbiased and consistent in the heteroscedasticity situation, they are not the optimal estimates. Thus, before performing any analysis, the heteroscedasticity of the model should be tested, and any heteroscedasticity should be eliminated. White's general heteroscedasticity test (WT) is the most widely used method to test for heteroscedasticity. In White's test, the null hypothesis is that the random error of the regression equation satisfies homoscedasticity. The alternative hypothesis is that the random error of the regression equation is heteroscedastic. The test statistics (WT) under the null hypothesis follows a χ^2 distribution with k degrees of freedom, where k is the number of independent variables. If $nR^2 > \chi^2(k)$, where n is the number of observations, R^2 is auxiliary regression determinability coefficient, then the null hypothesis is rejected, and there is evidence that the residuals are heteroscedastic (Xu et al., 2002). For heteroscedasticity tests, SAS can apply a procedure called PROC Model to analyse the dataset with '/white'. In econometrics, heteroscedasticity usually appears in the analysis of cross-sectional and panel data. In order to eliminate heteroscedasticity after White’s test, using the robust standard error is the most popular and effective method. Robust standard error solves that the standard deviation is not sensitive to possible heteroscedasticity problems in the model. The robust T statistic calculated based on the robust standard deviation is still asymptotically distributed. T test and F test for regression coefficient by robust standard error are both asymptotically effective. Thus, it will not influence the estimates for the regression (Mark, 2020). In order to calculate the robust standard error, SAS can apply procedure called PROC REG to calculate robust standard errors with '/acov'.

3.4.5.1 Robustness checks and endogeneity

In economic and financial empirical research, after selecting the research model, a robustness check can be applied to test if the original test is valid under other conditions. Robustness checks have become widely used in studies to ensure the scientific basis of the research (Kuorikoski, Lehtinen & Marchionni, 2007). For example, 23% of the papers published in 'The American Economic Review' during 2009 performed a robustness check (Lu & White, 2014).

In literature, robustness has been discussed by many researchers and defined in several different ways. For example, robustness can be defined as the same sign and significance, or as weighted averaged effect, or as effect stability for original and checked results (Neumayer & Plümer, 2017). In order to have higher robustness of the evaluation methods and the explanatory ability of indicators, a robustness check or robustness test could be applied. Hansen and Sargent (2008) suggested that based on the research purpose, the robustness check could be to:

- Adjust the classifications or standards to the data and test if the results are still significant.
- Replace, increase or reduce the independent variables to test if the results are still significant.
- Use another analysis method (e.g., fixed-effects panel data regression models or Generalised Method of Moments (GMM) models) to test whether the results are still robust.

Therefore, in order to test the consistency of the results, this research applies a different measurement method to test if the results are still similar.

Besides fixed-effects and random-effects model estimators, GMM model estimators are also important in econometrics research. Based on Hansen (1982), GMM is a parameter estimation method based on the fact that the actual parameters of the model meet a specific moment condition. In another words, suppose we have n observations $\{x_1, x_2, \ldots, x_n\}$ from a statistical model, and we know that the following q moment conditions hold, $E(m_1(x_1, \theta)) = 0, E(m_2(x_2, \theta)) = 0, \ldots, E(m_q\left(x_q, \theta\right)) = 0$, where θ is a p-dimensional unknown parameter for this statistical model. And it is defined as a q-dimensional moment function with respect to θ. So, $E(m(x_i, \theta) = 0$. Then if we give a q×q weight matrix W, then we have $E(m(x_i, \theta)' W m(x_i, \theta)) = 0$. Thus, The GMM estimate of $\hat{\theta}$ is $\hat{\theta} = \arg\min_{\theta \in \Theta} \sum_{i=1}^{n} m(x_i, \theta)' W m(x_i, \theta)$, where Θ is the space in which the parameter θ is taken. In econometrics, there are two types of estimation methods for GMMs, known as first-difference or one-step GMM and second-order or two-step GMM. The one-step GMM has limitations when estimating as it misses recent values. If a recent value is missed, then the first-difference transformation could result in the loss of too many observations which could lead to an inefficient estimation on the dataset, whereas two-step GMM could solve this as it prevents unnecessary data loss (Roodman, 2009). For two-step GMM, it also has limitations when estimating using small samples. Many studies with Monte Carlo methods found that the estimated asymptotic standard errors of the efficient two-step GMM estimators show severely downward bias in small samples whereas one-step GMM is virtually unbiased (Arellano and Bond, 1991). Although both methods show some limitations, the GMM estimators are known to be consistent, asymptotically normal, efficient and can produce unbiased estimates in all estimators, as GMM does not use any extra information but only employs valid internal instruments during estimation.

Some studies use GMM estimation methods to test the relationship between bank risks and bank performance. For example, Athanasoglou et al. (2008) applied a GMM technique to Greek banks which tested the effects of credit risks, operational risks and market risks to bank performance during 1985-2001. They found that higher credit risks, lower capital holdings and higher operational risks could lower the Greek banks' performance. Their study proved the importance of risk management and industry monitoring. Following a similar method, Tan (2016) used a one-step GMM to test the Chinese banks from 2003 to 2011. He found similar results, namely that higher credit risks and lower liquidity holdings could lower the Chinese bank performance. This suggested that, in order to have a better performance, both bank managers and regulators should improve risk management and monitoring efficiency.

Moreover, as mentioned above, many studies use a robustness check to test the validity of their original models. For example, both DeYoung & Jang (2016) and Fredriksson & Moro (2014) use random-effects panel data regression models to test the dataset and then use a GMM estimator to demonstrate robustness. In more detail, DeYoung & Jang (2016) tested the influence of liquidity risk management for US banks from 1992 to 2012. They showed that banks should follow and meet the legal liquidity requirement, which could help banks to perform better, and the GMM estimator confirm their findings received from their original models. Fredriksson & Moro (2014) tested the impacts of capital and liquidity risks for Finnish banks from 2001 to 2005. They showed that lower liquidity holdings and higher debt could damage bank performance. With the support of the GMM estimators, their original models were showed to be reliable. Therefore, following previous literature, a one-step GMM system estimator will be applied as a robustness check to test the validity of our models for China, the UK and Australia.

The general model to be estimated for our data is $y_{it} = \beta_0 + \sum_{j=1}^{k} \beta_j x_{jit} + u_{it}$, with $u_{it} = \alpha_i + \varepsilon_{it}$. where y represent the performance variables; x represents the risk variables and bank size; β_0 represents the constant term; $\beta_j\,(j = 1 \sim k)$ are coefficients to be estimated; i and t are indices for the sections and time, respectively; k is the number of independent variables; α_i is the bank-specific unobserved effect and ε_{it} is the error term. As our robustness check GMM model is motivated by the literature exploring the determinants of bank performance (e.g., Athanasoglou et al., 2008; Tan, 2016), we will include one lag of the dependent variable as an additional regressor following the literature. Thus employing a dynamic model, the model can be expressed as $y_{it} = \beta_0 + \delta y_{i,t-1} + \sum_{j=1}^{k} \beta_j x_{jit} + u_{it}$, where $y_{i,t-1}$ is a one-period lagged performance variable and δ is the speed of adjustment to equilibrium. The value of δ normally stays in the range of 0 to 1, which indicates that the performance persists and eventually, the value returns to the average level. A value close to 0 suggests a high speed of adjustment, while a value close to 1 suggests a slow adjustment (Athanasoglou et al., 2008). Moreover, as noted in 3.4.4.3, a dummy variable is added for Chinese traditional banks, which is SOB_{it} to show if the ownership influences the bank performance. Thus, an additional model for Chinese traditional banks can be expressed as $y_{it} = \beta_0 + \delta y_{i,t-1} + \sum_{j=1}^{k} \beta_j x_{jit} + \gamma SOB_{it} + u_{it}$, where γ is the coefficient of the dummy variable. The additional estimation results will be shown in Appendix 1 and 2.

In addition, endogeneity can be an issue in regression models. In econometrics, endogeneity occurs when the independent variable and the error term are correlated. There are three main sources from which endogeneity may occur. Firstly, the difference between endogenous and exogenous variables is based on a simultaneous equation model, in which the variables whose values are determined by the model are separated from the predetermined variables. As a result, ignoring simultaneity in the estimation will lead to biased estimates. It will cause a violation of the Gauss-Markov theorem in the exogenous hypothesis and lead to endogeneity. Secondly, correlation between the independent variable and the error term can also arise when an unobserved variable confounds both the independent and dependent variables. The third case is when the independent variables are measured with errors (Johnston, 1972; Wooldridge, 2009).

In general, if the independent and dependent variables of a model are mutually dependent, that will lead to endogeneity.

When analysing a data set through a regression model, Ordinary Least Squares (OLS) estimates of regression coefficients can be biased if the independent variables are related to the error term. As one of the main assumptions of OLS is that there is no correlation between the independent variables and the error term, these biases can lead to inconsistent estimates and incorrect inferences, which can lead to inappropriate conclusions and theoretical interpretations. Sometimes, such biases can even lead to coefficients having the wrong sign. Therefore, we need to apply tests to check for endogeneity problems. Besides helping to choose a model between fixed-effects or random-effects, the DWH test also helps us to detect correlation between variables in the regression model. As mentioned in section 3.4.5 above, the DWH test checks for correlation between the error term and the independent variables in the model, where the null hypothesis is that there is no correlation between the error term and the independent variables (Davidson & MacKinnon, 1993). Therefore, if the DWH test shows that the random-effects model is preferred, there is no endogeneity problem.

In order to solve endogeneity bias in panel data, GMM is one of the remedies to corrects for all three types of endogeneity, as it assumes that the error term is independently and identically distributed across the dataset (Zeafarian et al., 2017). GMM for dynamic panel data was developed by Arellano and Bond (1991) and Blundell and Bond (1998). In dynamic panel data, the cause and effect relationship for underlying phenomena is generally dynamic over time. For example, in banking risk management, it may not be the current year's risk factors that influence performance, but rather the previous year's risk factors that play a significant role. In order to address this situation, dynamic panel data estimation techniques use the lagged value of the dependent variables as an explanatory variable. Lagged values of the dependent variable are determined as instruments to control the endogenous relationship. As lagged variables are used in the existing model, they are often referred to as 'internal instruments' (Roodman, 2009). In more detail, the GMM model eliminates endogeneity by performing an internal transformation of the dataset through a statistical process that subtracts the past value of the variable from its present value. Because of this process, the number of observations is reduced and the efficiency of the GMM is enhanced (Wooldridge, 2009). Ullah, Akhtar and Zeafarian (2018) indicated that there are significant differences between OLS, fixed-effects and GMM estimations, due to endogeneity bias. By examining datasets from the marketing industry, they found out that GMM had better controls for endogeneity. Schultz, Tan and Walsh (2010) also found similar results with a governance-performance dataset. Thus, the one-step GMM we used for robustness checks can not only test the robustness of the models but also could reduce the possible issues caused by endogeneity.

3.4.6 Data analysis tools

For analysing data collected from the annual and interim reports, statistical software is needed. In this research, Microsoft Excel and SAS are the two main software packages used.

- Microsoft Excel

Excel has become the most widely used software for analysing data with basic models. It provides a straightforward way to record and analyse data. In this research, Microsoft Excel will only be used for recording and cataloguing data.

- SAS

SAS is widely used in many large companies. It uses a Sample, Explore, Modify, Model and Assess process, which offers a simple way to understand and assist in organisations' development and projects (Azevedo & Santos, 2008). There are many advantages of using SAS. Firstly, it is relatively easy to learn SAS coding. It is user friendly when people miscode or mistyping anything in the code program. SAS shows the error line for the user to debug. The error and warning messages are distinct and comprehensible to look at and re-code to make sure the whole program can run smoothly. Secondly, the SAS support website provides a range of useful suggestions which make it easier to learn and use SAS. Thirdly, it can protect the dataset security. Finally, it has an excellent capacity to handle all data, not only in the analysis procedures but also in the graphical procedures. Therefore, SAS will be used as the primary analysis tool in this research. The panel data analysis procedure (called PROC Panel) will be used for conducting measures of construct validity and reliability for the regression models.

3.5 Conclusion

In this chapter, research design and methodology were presented and employed. It detailed data collection methods and explained how these variables were selected and will be analysed in the following chapters. The research design highlighted the models used to show the effects of bank risks on their performance from different perspectives. Moreover, this chapter also provided sample selections for case studies which will enhance the understanding of both traditional banks and the fintech industry. It will help us to address the research questions and achieve the research aims.

We will use mixed methods to further the research aims. This followed some previous researchers (e.g., Geng et al.,2016; Jumono et al.,2016; Wu & Olson,2010) who used similar quantitative methods. This thesis will also provide case studies for particular samples to develop the context in the research area. It will also follow some previous researchers (e.g. Docherty & Viort, 2014; Howcroft, 2005; Rad, 2016) who use similar qualitative methods. We believe that by adopting a mixed methodology, we will achieve results relevant to both traditional banks and fintechs and offer value to them, particularly because there are rarely results comparing different types of banks. The detailed analysis and results for different countries are presented in the following chapters.

CHAPTER FOUR

RESULTS AND ANALYSIS

4.1 Introduction

Based on Chapter 2 (our literature review) and Chapter 3 (our research methodology), the research guide was designed to allow for analysis using both quantitative and qualitative methods. In this chapter, we will apply the analysis using descriptive statistics and panel data regression models. The results will be presented and compared by countries and bank' types. In more detail, we will investigate banks performance, through their financial reports, and consider aspects of risk management factors relating to differences between traditional banks and fintechs in China, the UK and Australia.

Thus, this chapter will present the results and analysis of the data obtained from our statistical analysis and will be organised as, Sections 4.2 to 4.4 present the aggregate analysis for each country, which including figure comparisons, descriptive statistics, stationarity, multicollinearity, homoscedasticity and endogeneity tests before regression estimations, random-effects regression models analysis and GMM tests for robustness analysis. Finally, Section 4.5 concludes the chapter.

4.2 Data analysis, results and discussion for China

In order to examine the relationship between bank risks and performance for Chinese traditional banks and fintechs, this section is organised as: 1. The bank performance and risk management of Chinese banks are presented in figures with presenting the differences between traditional banks and fintechs. 2. Descriptive statistics are listed and analysed. 3. The panel-data unit-root tests (Fisher's type) are applied to determine data stationarity. 4. Correlation matrix and variance influence factors (VIF) are presented to determine data multicollinearity. 5. White's test for heteroscedasticity, F test, Lagrange Multiplier Test and Durbin-Wu-Hausman (DWH) tests are applied to determine data endogeneity and appropriate regression approach to use. 6. The full analysis of random-effects panel data regression models is constructed based on bank type, which includes six models based on three dependent variables and two bank types. 7. The GMM estimates are applied and compared with results achieved from the panel data regression models. 8. Summary is applied for the section.

4.2.1 Comparisons between Chinese traditional banks and fintechs

Before presenting the panel data regression analysis, figures about bank performance and risk management between Chinese traditional banks and fintechs are presented based on semi-annual data. Figure 4.1 showed all three performance variables of Chinese traditional banks and fintechs. With regards to ROA, traditional banks showed signs of decreasing trends. Moreover, due to the pressure of China's decreasing economic trend and the regulations issued by the Chinese government in 2012 (CBRC, 2013), the trend shows a smooth decrease rather than a sudden drop. On the other hand, because of the new establishment of fintechs, it is easy to verify the growth trend for ROA. Unlike the smooth trend of traditional banks, extremes exist in the fintechs. Some fintechs started with extreme loss positions in their business. By developing in recent years, some of them passed the breakeven point, while some will make profits soon. A similar trend was presented in ROE. The reason could be that their calculation is similar, which is based on pre-tax profits divided by asset or equity, and equity is asset minus liability.

Concerning EPS, we notice a different situation. Firstly, because not all fintechs were in the stock market, we only present fintechs who have already joined. The EPS of each traditional bank fluctuates a small amount and stays smooth in the long-run. On the other hand, fintechs performed differently within companies, but the general trend shows increases. Some of them lost money at first and then continuously increased with positive EPS at the end of 2017. Some of them performed smoothly with a slight increase, which shows their smooth operations during these years. However, because of the short time since the fintechs' establishment and joining of the stock market, we should wait longer to see a comprehensive view of the performance in the stock market of Chinese fintechs. In addition, we could see that there are outliers for fintechs' ROA and ROE. Indeed, these points have much lower value than others. This suggests that in the infant stage of fintechs operations, these fintechs could have negative returns at different levels, but after this stage, they survived and began to have positive returns. Therefore, authorities could give fintechs chances even support them pass this stage.

Traditional Banks Fintechs

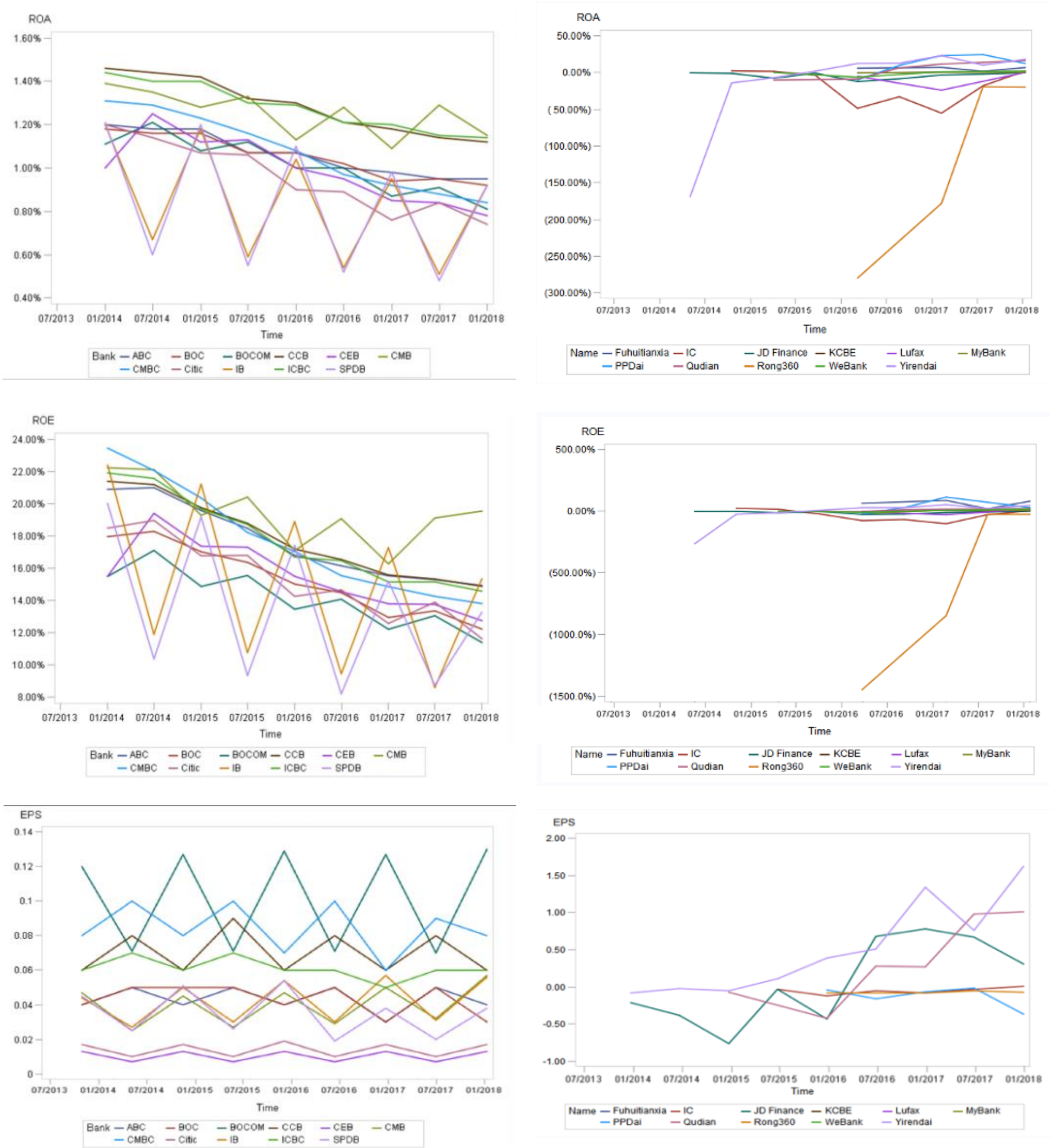
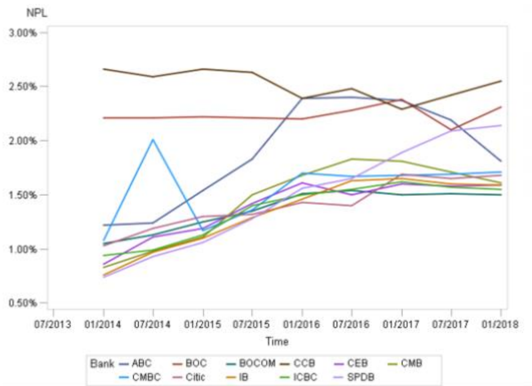


Figure 4.1 Performance Comparisons (China)

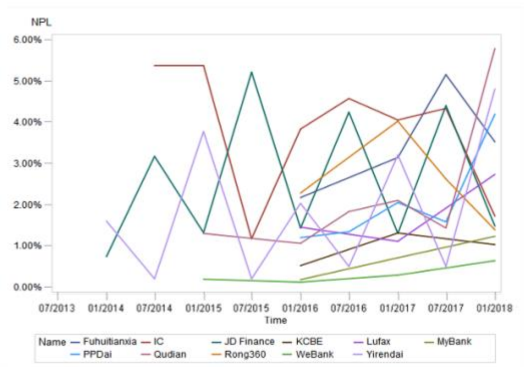
Figures 4.2 to 4.7 present the performance of independent variables, where Figure 4.2 shows credit risk variables; Figure 4.3 presents market risk variable; Figure 4.4 indicates liquidity and capital risk variables; Figure 4.5 shows reputational risk variable; Figure 4.6 indicates the operational risk variables and Figure 4.7 represents the banks' asset levels.

Because of the global fail in credit management, the risk of default by many banks increased. Although China's economy had been less affected than other countries, the NPL trend in both types of banks was increasing. However, the rate of traditional banks stayed relatively low and smoother. The possible reason might be that the fintechs had less choice with customers, and the traditional banks had more experience to deal with default loan. With regards to NCO, as mentioned in the methodology, it shows the charge-off rate over the three-year average. In order to have a better estimation for the future charge-off value, banks need to keep NCO smooth and low. Both types of Chinese banks had a relatively low rate. Some of them kept it at a low and smooth level for traditional banks, and some of the banks reduced it over time. For fintechs, the rate was volatile and a little bit lower than the rate in traditional banks, the reason for which could be that they were all established relatively recently, so there was not too much credit to write-off in outstanding loans. Concerning LoanR, all loss amounts in the total loan counts in this ratio based on its definition. All LoanR stayed under 10% with stabilised trends for traditional banks, which meant a smooth situation was achieved. However, for the fintechs, lines had positive trends, LoanR increased during these years with fintechs development. This indicates that credit risk management efficiency needs improvement because the consequences of continued neglect would be severe.

Traditional Banks



Fintechs



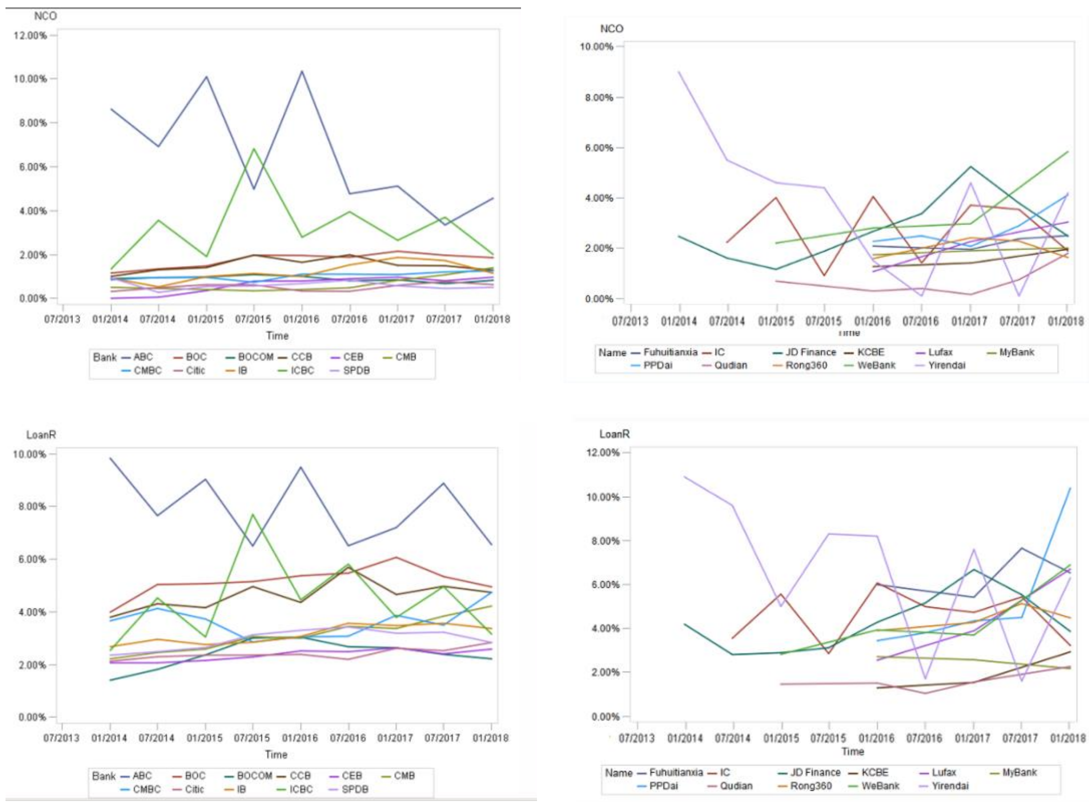


Figure 4.2 Credit risk variable comparisons (China)

Next, the market risk variable (VaR) was compared between traditional banks and fintechs in Figure 4.3. Most of the samples stayed in a tight range for traditional banks, which indicates that the market influence on traditional banks was relatively stable. However, there was one exception, BOCOM. Its VaR showed an increasing trend and have higher values than others. This indicates that BOCOM was more impacted by market risk than other traditional banks. Nevertheless, generally speaking, market risks had relatively less impact on traditional banks. For the Chinese fintechs, VaR also stayed in a tight range. However, as the scale of fintechs was much less than traditional banks, similar VaR values would lead to worse consequences. Thus, market risks impacted fintechs more than traditional banks. This result indicates that with more global connections, fintechs suffer more in market risk, even though they mainly operate in China.

Traditional Banks Fintechs

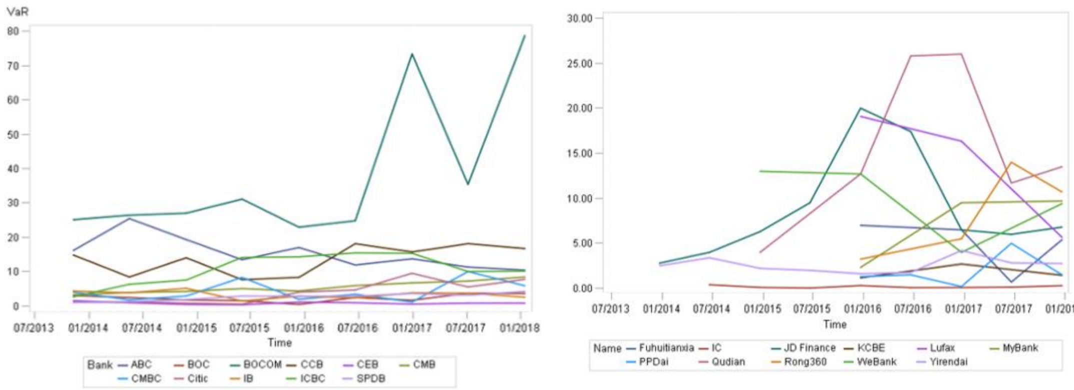


Figure 4.3 Market risk variable comparisons (China)

Figure 4.4 showed the five variables in capital and liquidity risks. With regard to LCR, the Basel accords required banks to achieve over 100% after 2015. For traditional banks, most of the samples achieved regulatory requirements. However, three traditional banks face short of liquidity coverage after 2015 with a less than 100% ratio. With warnings, these banks worked on solving the problem. As a result, their LCR increased over the following years and near the requirement. A similar situation was seen in the Chinese fintechs, as some of the fintechs had positions less than 100%. As they were still in the starting stage, the regulator was not that strict and allowed them to have more time to comply with the regulation. With the increased trends of these fintechs, it could be believed they would achieve the regulation requirements. Moreover, there is an outlier of LCR in the Chinese fintechs in Figure 4.4. It can be observed that Ideacome has much high liquidity compare with its expected cash flow. The reason to explain this is that the fintech received many liquidity investment at during that period. Therefore, the LCR back to the average level of Chinese fintechs.

With regard to CR, as it is designed to estimate banks' ability to recover current liability, the higher the ratio is the greater the banks' liquidity which indicates banks that have a better chance of meeting their current liabilities obligations. However, it should be kept at a reasonable level. As showed in the fintechs' figure, there is an outlier which is much higher than others. A too-high ratio may also lead to poor operation, as banks hold too many current assets to reduce operational efficiency. As the outlier is at the first year it published its data, this situation is accepted with reduce trend with its development. In addition, CR should be higher than one because the value of the ratio equal to one or above is an indication that the bank is in a stable position to cover its current liabilities. In general, for traditional banks, the ratio was higher than one and had a smoothly increasing trend. Some of the fintechs, on the other hand, had ratios less than one, which indicated that some fintechs had poor liquidity positions during some period.

Next, with regards to T1 capital ratio, as noted in our methodology, the minimum required ratio is 6% by the Basel Accords. For traditional banks, all of them achieved the required level and have signs of an increasing trend. On the other hand, for fintechs, most of them achieved the requirement. However, at their starting stage, some of them were not achieving 6%. Nevertheless, there is an outlier in the T1 figure. Webank had incredibly high T1. Similar to the Ideacome in LCR, the reason should be that Webank stayed in absorbing investment stage, with a high volume of investment in T1 capital, the ratio becomes very high. T1 of fintechs tended to have the average value in the industry. Thus, time should be given to fintechs to achieve better results.

The Chinese government revised the regulation on banks' debt level and asked them to publish their ratios in their annual reports (CBRC, 2015). The trend of D/A in traditional banks was then stabilised, which suggested that the debt level of Chinese banks was under control. On the other hand, because of the starting stage that fintechs are in, fintechs' debt levels were unstable. Moreover, the D/A value of some fintechs was higher than one, which suggested that these fintechs held too much debt which may influence their operational stability. With the development of business size, the D/A of fintechs could go near traditional banks' level in the future. And there is an outlier in Chinese fintechs' figure, Ideacome showed much higher D/A than others which proved its high debt level at the end of 2014, with a series of investment, it passed high debt stage and back to average level in Chinese fintechs. Similar to D/A, traditional banks had a stable trend in D/E. However, a different situation was presented in fintechs. At their starting stage of business, some of them even had a negative ratio which indicated that these fintechs had a negative net worth and financial instability. The development of these fintechs could solve this situation. When they achieve positive net values, the

D/E could become positive. Moreover, the figure also proves this result with an increasing trend in D/E from negative values.

Traditional Banks Fintechs

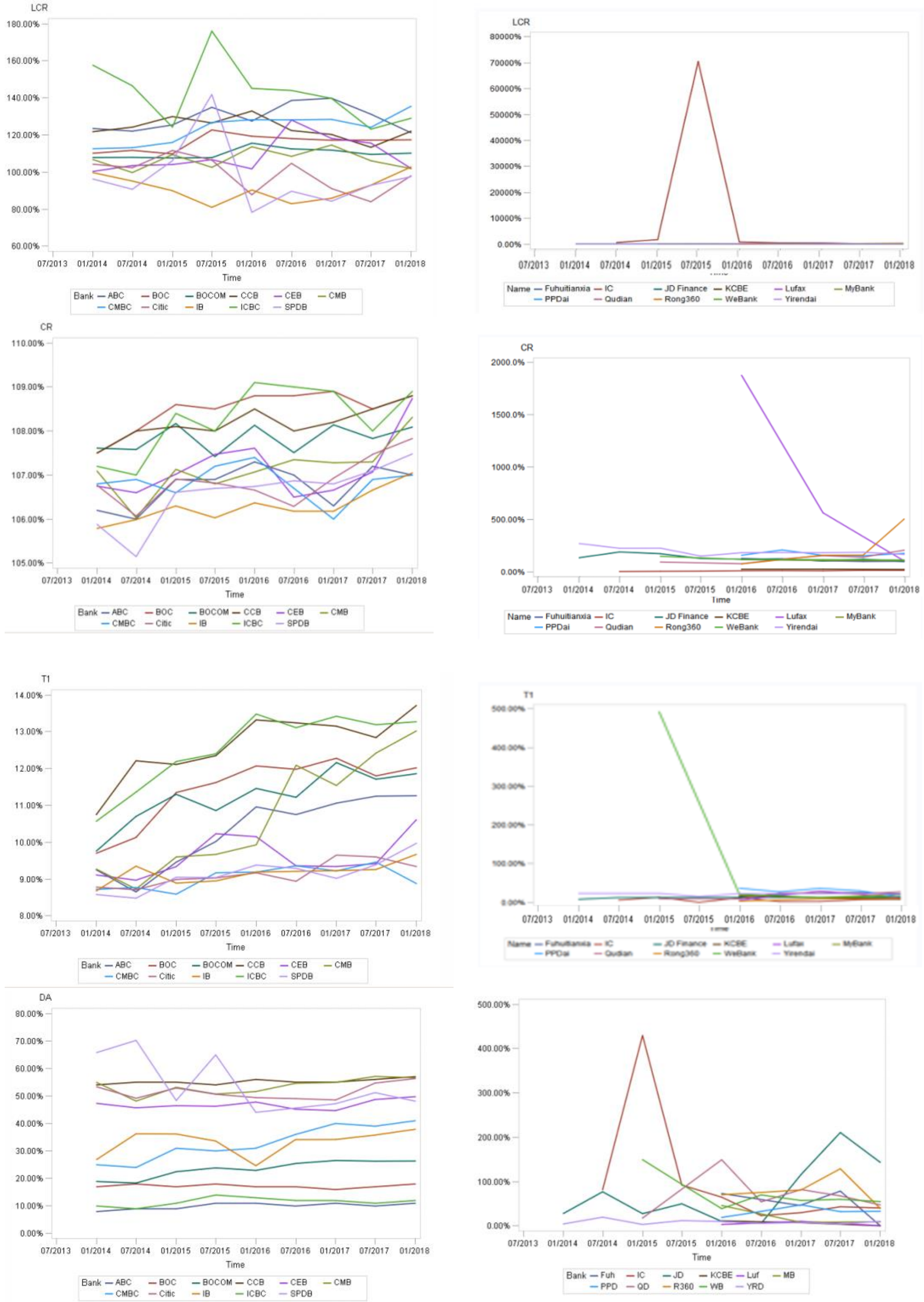


Figure 4.4 Capital and liquidity risk variables comparisons (China)

With regards to BVC in Figure 4.5, the trend for traditional banks moved by around 5%. This indicates that BVC for traditional banks was at an acceptable level as the overall value are increased. For the fintechs, the percentage was more volatile. Some of the fintechs had negative BVC, but some of them had large positive BVC. There is an outlier in Chinese fintechs' figure, it showed that from the end of 2016, QuDian increased it brand value much higher than other fintechs. In general, most of them had increasing brand value, and their future brand value could be expected to increase.

Traditional Banks | Fintechs

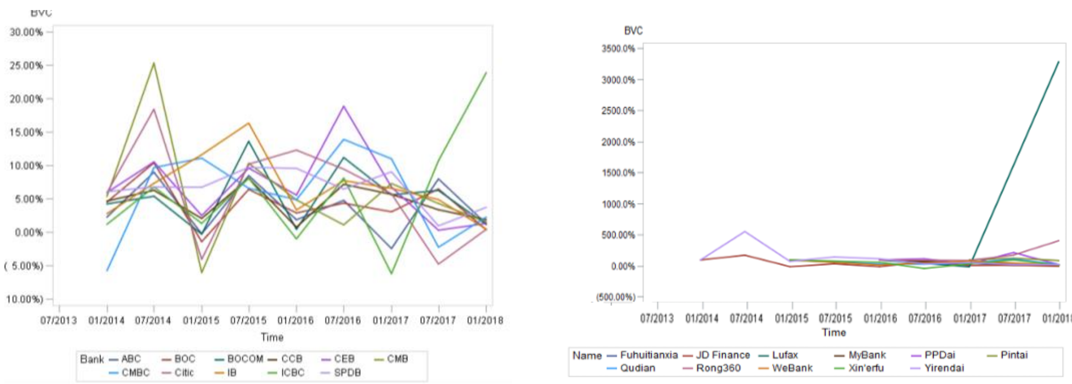


Figure 4.5 Reputation risk variable comparisons (China)

Figure 4.6 shows the operational risk variables. ORP showed a relatively smooth trend and remained at a low level for traditional banks. All ORP values were under 15%, which was lower than the requirement under the Basel Accords. This suggested that traditional banks could handle their operational risks when they occurred. However, some of the fintechs had over 15% ORP values. This suggests that these fintechs were in trouble with too many costs to solve operational risk issues. One extreme example was Ideacome. The China banking regulatory commission (CBRC) fined Ideacome almost $10 million because of illegal operations. However, it still survived through a series of big companies' investments (China Business and Finance, 2018). With regard to C/I, as mentioned in the literature review, a higher ratio shows a lower efficiency of banks' operations. For traditional banks, C/I stayed at a low level and tended to decrease too, which suggested that traditional banks were increasing their efficiency in operations management. For fintechs, C/I showed high values - some of them were over 100% - which suggested the cost of operation was higher than the income. For fintechs, the highest value showed in Lufax. Under a smoothing operating, the reason for high C/I should be an increased cost. As it planned to join the share market from 2015, an increasing operational cost was added which lead to a very high C/I. However, as fintechs were at the developing stage, a high C/I could be accepted with a decreasing trend. Thus, the C/I values of fintechs could decrease to a reasonable level in the future.

Traditional Banks

Fintechs

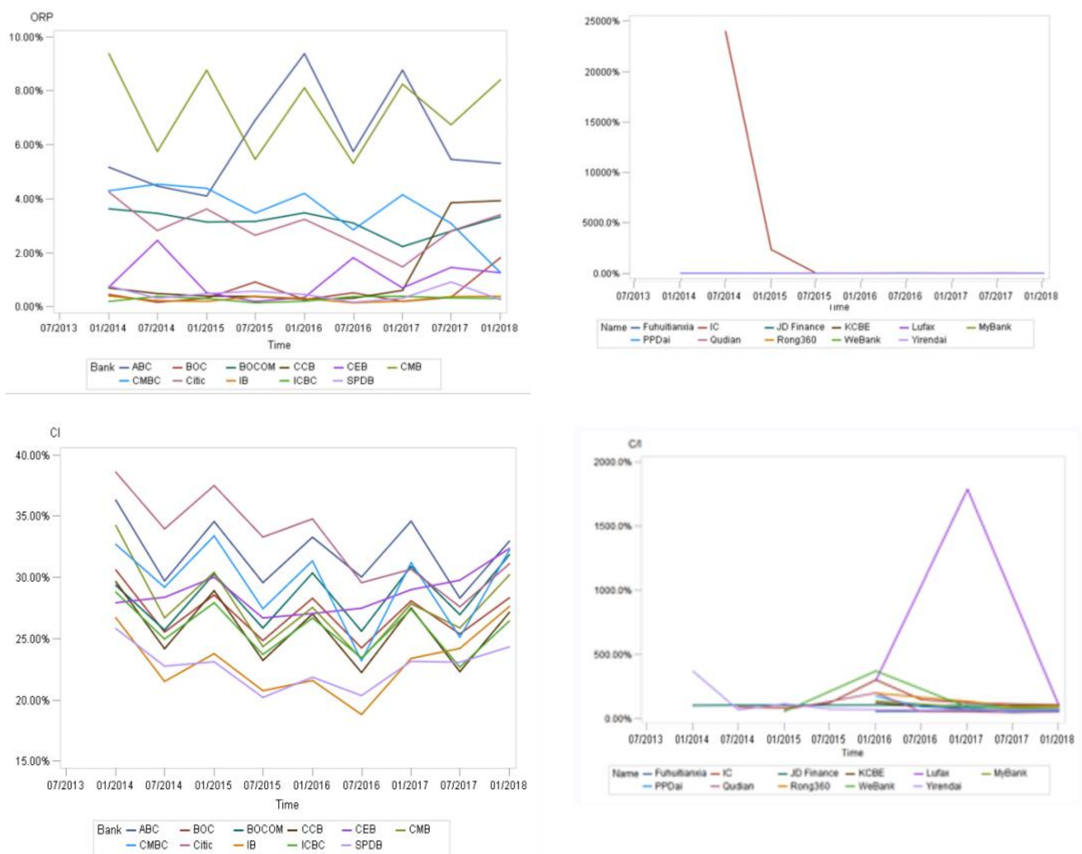


Figure 4.6 Operational risk variables comparisons (China)

Figure 4.7 shows the natural logarithm of the banks' assets. Both types of banks had increasing trends for their asset. This indicates that both types of banks developed during the investigation time period. The main reason for this is that even though the global financial system was still under the influence of the 2007-09 financial crisis, the Chinese financial system provided a good place to develop. However, the average asset level of fintechs was less than traditional banks which gives a higher potential for fintechs to develop.

Traditional Banks   Fintechs

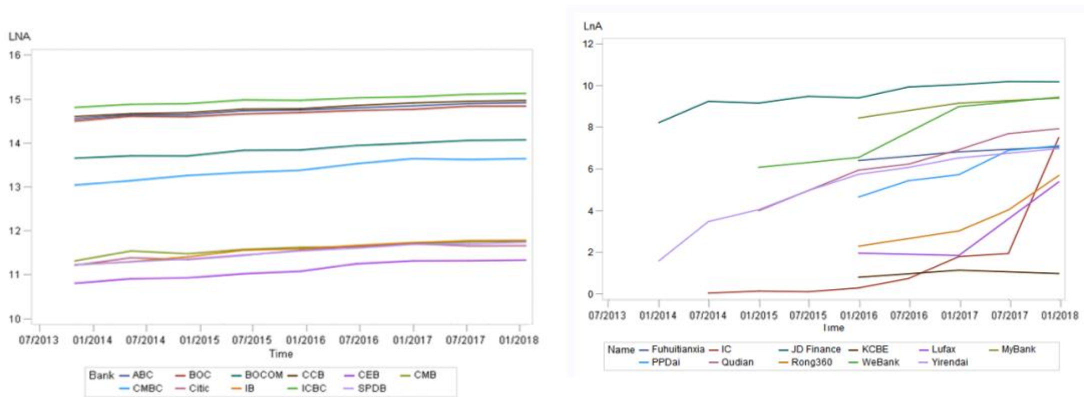


Figure 4.7 Bank size variable comparisons (China)

In general, traditional banks performed better than fintechs in both performance and risk management. One manifestation is outliers exist in fintechs' variables. The main reason for this could be that fintechs have just developed in recent years, and both the quality and quantity of customers were not at the optimum level. Therefore, analysing the differences and problems existing between traditional banks and fintechs, which could help managers to build better direction and focus for their risk management and future operations may be helpful.

4.2.2 Descriptive statistics

Tables 4.1 and 4.2 provide descriptive statistics for performance variables and risk variables based on types of bank.

With regard to ROA, the average was 1.06% for traditional banks, but -12.2% for fintechs. The negative average suggests that the performance of Chinese fintechs was weak and needs to improve. A similar situation happened for ROE. The average ROE for traditional banks was 16.31% and was -39.1% for the fintechs. This shows that, in general, traditional banks performed well with a consensus standard that the average of the S&P 500 had 14% ROE as an acceptable ratio. Even some of the fintechs (with a maximum of 114% ROE) performed well and developed a lot. The overall fintech performance was not as good as excepted.

On the other hand, with regards to performance in the share market, the average EPS of the traditional banks was $0.0496. Although the average was not very high, the earnings were more stable with a low standard deviation of 0.0294. For fintechs, although they did not perform that well in asset and equity levels, their performance in the share market was relatively well with mean $0.155. However, even though the average performance was better than traditional banks, the fintechs' EPS was more volatile with a 0.502 standard deviation. This means that investors had more chance to lose in the share market with the negative earnings (with minimum -$0.76), where the traditional banks had a positive minimum ($0.007).

In credit risk management variables, NPL stayed low. The average value was 1.64% in traditional banks, which meant that Chinese traditional banks had a low probability of default. The Chinese fintechs had a slightly higher NPL with 2.2%, which was 0.56% higher than traditional banks. This shows that the quality of the credit of fintechs was not high enough and that the number of customers was not large enough. With the lower customers' loyalty, quality and quantity, more movement was showed in fintechs' NPL, but given the development of the fintechs, a more stable NPL should be shown in the future. The second credit risk variable is NCO. The mean value was 1.69% for traditional banks. Similar to NPL, fintechs had a higher average value of NCO, which was 2.5%. During the investigated period, the rate peaked at 10.35% for traditional banks and 9% for fintechs which was at an acceptable level. During 2013-17, the US commercial banks' total loan reached the average value of 51% NCO (Federal Reserve System, 2018). Compared with the US, Chinese banks had a more stable and lower level of NCO. The last credit risk variable, LoanR, shows the overall credit risk performance. Both types of banks had a relatively low average level of the total loan loss ratio, 3.84% for traditional banks and 4.4% for fintechs. Moreover, fintechs had 0.54% bigger volatility than traditional banks. The peak level was 10.9% for fintechs versus 9.83% for traditional banks. This shows that even though the average performance looks similar, fintechs' credit risk management was more unstable and risky. They should increase credit risk management efficiency to keep operating and achieve better results.

With respect to the market risk, the average VaR was 9.13 for traditional banks and 6.3 for fintechs. This means, on average, market risks impacted more on traditional banks than fintechs in China. However, with a market share lower level, the influence should be stronger in fintechs as noted in the figure comparisons.

Following the Basel Accords, banks were required to apply their LCR to show their liquidity ability. Basel III asked banks to have a LCR of at least 100% from 2015 (BCBS, 2013) to ensure they have the necessary assets to survive any short-term liquidity disruption. Similar to the figure comparisons, the average value of LCR was 113.55% for traditional banks which met the legal requirement. However, the minimum was 78.31% which was lower than the requirement. As noted before, banks with this issue worked on solving it and tried to meet the legal requirement. For fintechs, the average ratio was 177% which was higher than traditional banks. However, the minimum value was 18% which was extremely low and showed that some fintechs were lacking in liquidity at some points during the investigated time period.

The average CR value was 107.3% for traditional banks, which shows that traditional Chinese banks had significant liquidity to cover their current liabilities. Also, CR had a 0.0088 standard deviation, which means that traditional Chinese banks always had enough liquidity to deal with emergency liquidity problems. For fintechs, the average CR was 162% which was high, but it was caused by the extreme value (the maximum 1876%), without extremes, the average CR drops to 132.99%. Although the liquidity situation of Chinese fintechs seems better, with the large standard deviation, a Chinese fintech might face the problem that sometimes it has too much liquidity and sometimes it is short of liquidity. This confirms the result showed in LCR as low values exist, the liquidity level overall for fintechs was not good enough. Then with regard to T1 capital ratio, all traditional banks meet the T1 requirement with the minimum 8.48%, which indicates that Chinese traditional banks had enough tier one capital to prevent bankruptcy. However, some of the fintechs did not perform that well in tier one capital where the minimum value was 2%. The existence of low values exposed the poor preparation of fintechs with regard to capital. Therefore, managers should plan to have more tier one capital in the future to meet the requirement and prevent bankrupting.

The last two liquidity and capital risk variables are D/A and D/E. As mentioned before, the difference between them is the denominator where D/E is total debt over the total equity, and D/A is over the total assets. For both ratios, higher ratios indicate that banks may have incurred a higher level of debt and that banks may not be able to repay their debt with the sustained cash flow. Traditional banks and fintechs had an average D/A at 35.42%, and 59.42%, representatively, which shows that fintechs had a higher level of debt and stayed in a more risky situation. With regards to D/E, the average was 5.3554 for traditional banks and 1.479 for fintechs. Higher values indicate that assets are more funded by their debt than equity and the D/E for banks usually higher than two, which can be confirmed for the traditional banks. Another reason for fintechs having a lower average value of D/E was that negative values exist (the minimum is -20.789). It indicated a negative net value existed in fintechs which should be unacceptable. Thus, regulators need to be more concerned about the fintechs that had negative values, monitoring their performance. If they still perform poorly, these fintechs face continuous loss and may need to exit the market. Investigations of these fintechs should be applied by the regulators to see possible solutions for helping these companies.

With respect to the operational risks, as noted before, if the ORP value is less than 15%, then traditional banks and fintechs are fine to deal with their operational risks. However, if the value is higher than 15%, they may not be prepared or earn enough money to deal with such issues, which may cause serious consequences. The mean value for traditional banks was about 2.46%, which was a low and well-performing position.

However, for fintechs, because of the existence of extreme values, the mean value of fintechs' ORP became 460.9%. However, without extreme values, the mean became 5.19% which was an acceptable level. The result means that fintechs face more operational risks than traditional banks. One possible reason could be that fintechs need to face more digital operational issues than traditional banks. Generally speaking, without extremes, operational risk management stayed at an acceptable level for both types of banks. To achieve a better understanding of operational risk, following Diallo et al. (2015), we also collected the C/I ratio to compare. In general, lower C/I ratios indicate more profitable bank performance. The average C/I was 27.67% for traditional banks and 137.3% for fintechs. This shows that traditional banks were more profitable than fintechs and that the costs in operations were more controlled for traditional banks than fintechs. Moreover, the maximum ratio was 1788% for fintechs which shows that for some fintechs, their costs were for higher than their income. Managers should either increase their income or decrease their operational costs (including operational risk costs) to solve this issue.

For the reputational risk variable, both types of banks had a positive percentage on average. However, the BVC of traditional banks was more stable with a 0.0559 standard deviation while the fintechs' BVC values were varied with a 4.308 standard deviation. This means that the brand value of fintechs changed a lot during their development. In addition, the mean value of the Chinese traditional banks' size was about US$475 billion with ln(asset) equal to 13.071. The average value of the Chinese fintechs was only about US$0.275 billion, with 5.615 in ln(asset). The relatively large difference in scale between them is also reflected in the banking industry's market place. As noted before, traditional banks hold more of the marketplace, but as fintechs develop, they gained nearly a 30% market share in the Chinese financial industry (Men, 2018).

Variable	Mean	Std Dev.	Maximum	Minimum
Return on asset	0.0106	0.0022	0.0146	0.0048
Return on equity	0.1631	0.0341	0.2344	0.0822
Earnings per share	0.0496	0.0294	0.1300	0.007
Non-performing loan ratio	0.0164	0.0049	0.0266	0.0074
Net Charge-off rate	0.0169	0.0193	0.1035	0.0001
Total loan loss ratio	0.0384	0.0176	0.0983	0.0141
Value at risk	9.1296	12.3828	78.7	0.300
Liquidity coverage ratio	1.1355	0.1741	1.760	0.7831
Current ratio	1.0731	0.0089	1.091	1.0515
Tier 1 capital ratio	0.1045	0.0152	0.1371	0.0848
Debt-to-Asset ratio	0.3532	0.1748	0.7016	0.0800
Debt-to-Equity ratio	5.3554	2.79	12.63	1.3363
Brand value change %	0.0559	0.0559	0.253	-0.0615
Operational risk %	0.0246	0.0253	0.0937	0.0015
Ln(Asset)	13.071	1.5536	15.131	10.8051
Cost-to-Income ratio	0.2767	0.0406	0.3858	0.1882
Observations			99	

Table 4.1 Descriptive statistics (Chinese traditional banks)

Variable	Mean	Std Dev.	Maximum	Minimum
Return on asset	-0.122	0.500	0.248	-2.798
Return on equity	-0.391	2.242	1.140	-14.461
Earnings per share	0.155	0.502	1.620	-0.760
Non-performing loan ratio	0.022	0.016	0.058	0.001
Net Charge-off rate	0.025	0.016	0.090	0.001
Total loan loss ratio	0.044	0.023	0.109	0.010
Value at risk	6.334	6.435	26.000	0.040
Liquidity coverage ratio	1.771	1.563	8.640	0.180
Current ratio	1.620	2.499	18.764	0.088
Tier 1 capital ratio	0.42	0.631	4.921	0.020
Debt-to-Asset ratio	0.5942	0.8037	3.4575	0.0123
Debt-to-Equity ratio	1.479	5.246	28.490	-20.789
Brand value change %	1.478	4.308	32.880	-0.108
Operational risk %	4.609	31.599	240.000	0.000
Ln(Asset)	5.615	3.087	10.191	0.050
Cost-to-Income ratio	1.373	2.316	17.884	0.445
Observations			58	

Table 4.2 Descriptive statistics (Chinese fintechs)

Notes: Not all Chinese challenger banks/fintechs are listed, observations are 39 for EPS. Without extreme values, Mean of ORP is 5.19%, S.D. is 0.076, Maximum is 0.3133, Minimum is 0.

Through understanding the descriptive statistics, we concluded that Chinese traditional banks' performance and risk management were moderately concentrated, but that the fintechs were unstable and varied between entities. Because of their unstable performance, it makes them more valuable to investigate which could help them to improve their performance in the future.

4.2.3 Panel data unit root test

As described in Chapter 3, before applying the regression model, we need to test the stationarity, multicollinearity and endogeneity of the data and select the appropriate modelling approach. First, we apply a unit root test for panel data to test the stationarity of the data set. To test the stationarity of the data, Fisher-type unit root tests were implemented based on ADF tests. The null and alternative hypotheses are H_0 is that the data are non-stationary or have unit roots, and H_1 that the data are stationary or do not have unit roots. The results of the unit root based on bank type are shown in Table 4.3. The results show that all variables are stationary at the 1% level of significance. The null hypothesis for the variables is rejected, indicating that there is no evidence of unit roots and the data are stationary.

	Traditional banks		Challenger banks/fintechs	
Variable	Statistics	P-value	Statistics	P-value
ROA	36.30	0.000	35.54	0.000
ROE	34.22	0.000	26.46	0.000
EPS	79.56	0.000	13.65	0.000
NPL	51.37	0.000	14.99	0.000
NCO	72.41	0.000	18.03	0.000
LoanR	49.04	0.000	26.00	0.000
VaR	55.96	0.000	42.04	0.000
LCR	91.18	0.000	20.72	0.000
CR	48.34	0.000	27.52	0.000
T1	40.79	0.000	28.36	0.000
D/A	51.29	0.000	32.30	0.000
D/E	146.75	0.000	23.67	0.000
BVC	59.13	0.000	12.87	0.000
ORP	44.81	0.000	25.25	0.000
Ln(Asset)	91.39	0.000	28.11	0.000
C/I	25.17	0.000	29.25	0.000

Table 4.3 Fisher-type unit root tests (China)

4.2.4 Correlation matrix and variance inflation factors

When there is a high degree of correlation between two or more independent variables, the estimates can be misleading, and even the conclusions of the estimated model may be wrong. Therefore, the assumption to follow is that the independent variables are independent of each other. To do so, having tested the stationarity of the variables, the next step is to test for the presence of multicollinearity between the independent variables. Tables 4.4 and 4.5 provide the cross-correlation coefficient matrices for each of the independent variables based on bank types. According to Gujarati (2003), if the correlation coefficient of each of two regressors exceeds 0.8, there may be a multicollinearity problem. As all figures are below 0.8, there is no multicollinearity problem in this study.

	NPL	NCO	LoanR	VaR	LCR	CR	T1	D/A	D/E	BVC	ORP	LnA	C/I
NPL	1												
NCO	0.1914	1											
LoanR	0.4825	0.6450	1										
VaR	0.0377	0.1902	0.0860	1									
LCR	0.2325	0.4923	0.5057	0.1565	1								
CR	0.5129	0.0555	0.1830	0.2741	0.3757	1							
T1	0.5312	0.2104	0.3362	0.3730	0.4736	0.6578	1						
D/A	-0.0295	-0.5970	-0.5258	-0.2687	-0.4409	-0.2454	-0.2365	1					
D/E	-0.1579	-0.5916	-0.5523	-0.3303	-0.4962	-0.4155	-0.3896	0.6476	1				
BVC	-0.1695	-0.1295	-0.1481	-0.1063	-0.1088	-0.2947	-0.1913	0.0642	0.1461	1			
ORP	-0.0398	0.2352	0.2032	0.1548	0.0785	-0.1657	-0.0648	0.0131	0.0001	-0.1093	1		
LnA	0.5261	0.5456	0.6495	0.3993	0.6962	0.5928	0.6763	-0.6518	-0.7399	-0.1503	-0.0285	1	
C/I	-0.1067	0.2095	0.1071	0.1310	0.1542	-0.0270	-0.1617	-0.1145	-0.1212	-0.2633	0.4958	0.0529	1

Table 4. 4 Cross Correlation Matrix (Chinese traditional banks)

	NPL	NCO	LoanR	VaR	LCR	CR	T1	D/A	D/E	BVC	ORP	LnA	C/I
NPL	1												
NCO	0.309	1											
LoanR	0.544	0.763	1										
VaR	-0.211	-0.392	-0.319	1									
LCR	0.081	0.023	0.106	-0.126	1								
CR	-0.087	-0.098	-0.068	-0.063	0.352	1							
T1	-0.163	-0.021	-0.071	-0.038	-0.081	-0.039	1						
D/A	0.249	0.107	0.027	-0.072	-0.112	-0.104	-0.065	1					
D/E	-0.224	0.186	-0.174	0.102	0.001	0.025	0.001	0.131	1				
BVC	-0.056	-0.135	-0.003	-0.063	-0.156	0.235	-0.062	-0.230	-0.207	1			
ORP	0.184	-0.008	-0.037	-0.066	-0.143	-0.010	-0.046	0.029	0.027	-0.090	1		
LnA	-0.090	-0.073	-0.059	0.350	-0.255	-0.210	-0.025	-0.191	0.014	0.074	-0.292	1	
C/I	0.143	0.475	0.353	-0.298	0.239	0.040	-0.066	0.422	0.099	-0.130	-0.018	-0.224	1

Table 4.5 Cross Correlation Matrix (Chinese challenger banks/fintechs)

However, we could see that there are some relatively high correlations (close to and over 0.7) that exist between independent variables in matrices showed above. Thus, we will apply VIF for our dataset to double-check for multicollinearity problems. The VIF ranges from 1 upwards, and the value shows the percentage by which the variance is inflated for each coefficient. Generally, a VIF equal to 1 indicates no correlation, a VIF between 1 and 5 indicates a moderate correlation, and a VIF above 5 indicates high correlation. In addition, a value over 10 VIF indicates a too high correlation and can be a cause for multicollinearity concern (Dodge, 2008). Table 4.6 presents the VIFs for all variables based on types of banks. From Table 4.6, we found out that NCO and Ln(asset) for traditional banks and LoanR for fintechs are relatively larger than others. This shows that these variables have a relatively higher correlation with other independent variables. Moreover, as credit-related variables show a relatively higher correlation with other variables in both types of banks, which indicates higher interactions between credit-related variables and other risk management variables. This suggests the importance of credit risk management for both types of banks. Managers should pay more attention to these variables to prevent to much movement to other risk variables. In summary, as all VIFs are below 10, the results double-check the correlation matrix results and indicate that there are no issues of multiple correlation in this study.

Variable	Traditional banks	Challenger banks/fintechs
NPL	3.490	2.467
NCO	4.564	3.646
LoanR	3.684	4.896
VaR	1.949	1.530
LCR	1.441	1.529
CR	2.282	1.468
T1	4.345	1.121
D/A	2.617	1.290
D/E	2.371	2.180
BVC	1.283	1.997
ORP	2.950	2.161
Ln(Asset)	4.699	1.979
C/I	3.105	1.615

Table 4.6 Variance inflation factors (China)

4.2.5 Tests for heteroscedasticity, endogeneity and model determination

After stationarity and multicollinearity were tested, heteroscedasticity and endogeneity of the dataset need to be tested. As noted in Chapter 3, in data analysis, if the error terms do not have constant variance, they are heteroscedastic. If heteroscedasticity is present, the standard errors are biased. This can lead to bias in test statistics and confidence intervals. In order to test for heteroscedasticity, White's general heteroscedasticity test is employed and the results are shown in Table 4.7. The results of White's test show that heteroscedasticity is present. Since heteroscedasticity causes standard errors to be biased, after finding the proper static panel model, we used robust standard errors.

	Bank type	ROA model	ROE model	EPS model
			p-values	
White's test	Traditional banks	0.0000	0.0000	0.0000
	Fintechs	0.0003	0.0004	0.0000

Table 4.7 Tests for heteroscedasticity

As mentioned in Chapter 3, the DWH test needs to be applied to test the endogeneity before analysing the panel regression results. The null hypothesis H_0 is $E(e_{it}, x_{it}) = 0$, which indicates that there is no endogeneity in the dataset. The alternative hypothesis H_1 is $E(e_{it}, x_{it}) \neq 0$, which indicates that at least one independent variable is an endogenous variable. From Table 4.8, we can see that there is no endogeneity problem for this study.

Besides testing for endogeneity, the DWH test also helps to select the appropriate approach to analyse the panel data from fixed-effects or random-effects, where H_0 suggests the random-effects model is more appropriate and H_1 suggests the fixed-effects model is more suitable in this research. In addition, the F test and Lagrange Multiplier test were used to determine whether the pooled OLS, fixed-effects or random-effects model was the most appropriate for this study. The F test was applied to analyse the applicability of the panel with fixed-effects compared to pooled OLS, whereas the Lagrange Multiplier test analysed the applicability of a panel with random-effects compared to pooled OLS. In both tests the null hypothesis suggests the pooled OLS is more appropriate, and the alternative hypothesis suggests fixed-effects or random-effects is more appropriate. Together with the DWH test, the choice between fixed- and random-effects was determined.

The results for all three tests are shown in Table 4.8. It can be observed that random effects proves to be the most appropriate approach for both types of bank. The F test and Lagrange Multiplier test show that models with fixed- and random-effects are more appropriate than pooled OLS with zero p-values for all dependent variables and bank types. Since both models were valid, the Hausman test was performed and results showed that a model with random-effects is more suitable than fixed-effects, with p-values over 5% for three dependent variables and both types of banks. Furthermore, we see that the ROA and ROE model for traditional banks has a p-value close to 5%. According to Torres-Reyna (2007), even though the p-value is only near to the significance level, we still cannot reject H_0 and need to use random-effects models for the ROA and ROE.

Test	Bank type	ROA model	ROE model	EPS model
		p-values		
F	Traditional banks	0.0000	0.0000	0.0000
	Fintechs	0.0000	0.0000	0.0000
LM	Traditional banks	0.0000	0.0000	0.0000
	Fintechs	0.0000	0.0000	0.0000
DWH	Traditional banks	0.0812	0.0632	0.1698
	Fintechs	0.1931	0.3153	0.3573

Table 4.8 Tests for determination the most appropriate approach for data analysis (China)

4.2.6 Panel data regression analysis

As mentioned above, random-effects models are more suitable here. Based on three dependent variables, six models are constructed to examine the relationship between bank risks and bank performance for Chinese traditional banks and fintechs. The random-effects model estimation results are shown in Tables 4.9 to 4.11.

Firstly, ROA was selected as the dependent variable to establish two random-effects panel data regression models based on bank type. We attempted to evaluate the effect of different risk management variables on ROA. The results are presented in Table 4.9 below. Regarding the types of banks, we can see that while the differences are apparent among the estimated coefficients, only some of the variables are significant. The reason for selecting more variables was because both differences and similarities existing in the results can be shown between traditional banks and fintechs.

	Traditional banks		Fintechs	
	Estimations	Robust Std. Err	Estimations	Robust Std. Err
Intercept	0.0386	0.0641	-0.3137	0.2229
Non-performing loan ratio	-0.1569*	0.0670	-1.2489*	2.7662
Net Charge-off rate	-0.0172	0.0257	-7.270**	3.8563
Total loan loss ratio	-0.0279*	0.0327	-2.6522	2.6178
Value at risk	-0.0001	0.000023	-0.0043*	0.0077
Liquidity coverage ratio	0.0004*	0.0017	0.0001	0.0971
Current ratio	0.0278	0.0611	0.0115*	0.0191
Tier 1 capital ratio	0.0299**	0.0326	0.0355	0.0624
Debt-to Asset ratio	-0.0007	0.0115	-0.6547***	0.1308
Debt-to-Equity ratio	-0.0002*	0.0007	0.0089	0.0086
Brand value change %	0.0025***	0.0035	0.0020	0.0130
Operational risk %	-0.0037*	0.0142	-0.0014	0.0707
Ln(Asset)	-0.0002***	0.0005	0.1249***	0.0243
Cost-to-Income ratio	-0.0147	0.0069	-0.0155**	0.0211
R^2_{within}	0.3120		0.6997	
$R^2_{between}$	0.3602		0.7707	
$R^2_{overall}$	0.2769		0.4723	
No. of Obs.	99		58	

Table 4.9 Random-effects estimation results (ROA, China)

Note: *, **, ***represent significance at the 10%, 5% and 1% levels respectively.

For traditional banks, all credit risk variables negatively influence ROA, where NPL and LoanR are significant at the 10% level. This suggests that higher credit risks would lead to worse ROA, and only NPL and LoanR significantly and negatively influence the ROA. In the credit risk variables, the NPL has the largest coefficient and a 1% change of the NPL will lead to a 0.1569% change in ROA while a 1% change in NCO and LoanR lead to a 0.0172% and 0.0279% change in ROA respectively. This suggests that managers should pay more attention to NPL during credit risk management, as NPL not only significantly influences the ROA, but also has a higher coefficient. Similar to Kerkhof et al. (2010), VaR also has a negative estimate. But as it is not significant, combined with a relatively stable financial situation in China, traditional banks can worry less about the impact of market risk on ROA.

Regarding the capital and liquidity risk variables, LCR and T1 have significant positive impacts on ROA with 10% and 5% respectively. This suggests that increased tier one capital and liquidity holding percentage in the traditional banks would improve their asset performance. T1 had a higher significance level, suggesting that managers should pay more attention to ensure T1 meets the requirement. Even though the CR does not significantly influence the ROA model, with its positive influence, managers should keep the CR at a healthy level to help them achieve a better ROA. Concerning debt level, D/E has a negative and significant at the 10% level impact on ROA, which suggests that an increased debt level in traditional banks would reduce their ROA performance. As with D/E, D/A negatively impacts the ROA for traditional banks with a stronger influence based on its higher coefficient value. Even though only D/E shows significance, managers should keep the debt level relatively low which to help banks attain better performance.

For selected operational risk variables, both affect ROA negatively with a higher risk level, where ORP is significant at the 10% level. Based on the coefficient values, a 1% increase of ORP or C/I will lead to 0.0037% or 0.0147% of the decrease in ROA respectively. Even though change in C/I will changes ROA more, the higher significance level of ORP suggests that Chinese traditional banks should pay more attention to particular operational issues than overall operational costs. In light of Figure 4.6 and Table 4.1, traditional banks should pay more attention to ORP because Chinese traditional banks have a smooth and low C/I during the investigated time period. We can expect they will keep their C/I low and stable, so they need to focus more on particular operational issues than overall costs.

For reputational risks, the BVC shows its significant positive impact on ROA at the 1% significance level, and a 1% increase in BVC will lead to a 0.0025% increase in ROA. This suggests that increasing banks' reputation could help them increase their ROA performance. Thus, Chinese traditional banks should aim to have a good reputation during operations. At last, ln(asset) has a negative impact on ROA at the 1% significance level, where a 1% increase of ln(asset) will lead to a 0.0002% decrease to ROA. This means that a higher asset level will reduce bank performance and has a high level significance. This study confirms previous studies (e.g. Geng, 2016, Tan, 2016 and Zhang, 2010), which also found a negative relationship between ln(asset) and ROA. Thus, the result suggests that maintaining or decreasing the safety amount of assets could help traditional banks perform better in ROA.

For the fintechs, as with traditional banks, all credit risk variables have negative impacts. However, the significant variables are different where the NPL and NCO are significant at the 10% and 5% level respectively. Because of the higher significance level of NCO, managers should be more concerned about it than other credit risk variables. In the credit risk variables, the NCO has the largest coefficient and a 1% change of the NCO will lead to a 7.27% increase in ROA where NPL and LoanR lead to a 1.25% and 2.65% increase per 1% change representatively. This suggests that managers should pay more attention to NCO during credit risk management, as NCO not only significantly influences the ROA, but also has a high coefficient value. Moreover, the values of the estimates are much larger than they showed in traditional banks. This confirms that credit risk hurts ROA performance like traditional banks, but fintechs should be more concerned about these credit risk variables. One possible reason for this may be that traditional banks' credit risk management methods operate smoothly with their long history, whereas fintechs are still searching for suitable credit risk management methods.

With regards to market risk, VaR for fintechs shows the same impact as traditional banks, where a 1% increase in VaR will lead to 0.0043% decrease of ROA. Because VaR has higher impact rate and significance at the 10% level, the market risk seems more important to fintechs than traditional banks. In addition, based on the operational mechanisms, fintechs are more related to other markets than traditional banks in China. Thus, fintechs should take more care about market risk with their relatively weak market position in the financial system. Concerning the capital and liquidity risk variables, different results are shown. Only CR has a 10% significantly positive impact, but not like traditional banks where LCR and T1 are significant. In more detail, a 1% change in CR will lead to 0.0115% positive change of ROA, where LCR shows 0.0001%, and T1 shows 0.0355% positive changes to ROA. This means that fintechs need to pay more attention to keep their liquidity level healthy like traditional banks. Concerning debt level, D/A has 1% significantly negative impact, where a 1% change in D/A will lead to 0.65% negative change in ROA. Thus, this suggests that fintechs need to control their debt level. Moreover, as there existed negative equity in fintechs, the D/E estimation may not show the expected impact on ROA. Thus, the importance of D/A is seen, which is proved by the 1% significant level. This suggests that managers should consider more on D/A when managing risks.

For operational risk impacts, both variables also negatively impact ROA, where a 1% change in ORP will lead to 0.0014% negative change, and C/I shows 0.0155% negative impact. Unlike traditional banks, the cost of occurred risks (ORP) does not significantly influence ROA performance, but overall operational cost influences their performance at the 5% significance level. This suggests that fintechs need to control their overall costs and increase their operational efficiency to achieve better ROA performance. For reputational risks, the BVC shows its positive impact on ROA, a 1% increase in BVC will lead to a 0.002% increase in their ROA. This suggests that increase fintechs' reputation could help them increase their ROA performance. Although BVC does not significantly impact the ROA, increasing reputation during operations is still good for Chinese fintechs' ROA. Moreover, as fintechs are in their developing stage, unlike traditional banks, there is evidence of a positive relationship between bank size and ROA, which suggests that increasing size tends to result in higher returns on assets. Based on coefficient value, a 1% increase in ln(asset) will lead to 0.1249 % increase in ROA. This result is the opposite for traditional banks. Thus, in order to have a higher ROA, managers should control or increase the bank size in different types of banks.

Besides interpreting variables, we looked the R^2 (e.g., within, between and overall) for our ROA models. R^2(within) refers to the variation within one individual over time, which can be given by $R^2_{Within}(\hat{\beta}) = Corr^2[\hat{y}_{it} - \hat{y}_i, y_{it} - \bar{y}_i]$. R^2(between) measures the variation between the individuals, which is given by $R^2_{between}(\hat{\beta}) = Corr^2[\hat{y}_i, \bar{y}_i]$. R^2(overall) is a weighted average of these two, which is given by $R^2_{overall}(\hat{\beta}) =$

$Corr^2[\hat{y}_{it}, y_{it}]$, where $\hat{y}_{it} = x'_{it}\hat{\beta}$, $\hat{y}_i = x'_i\hat{\beta}$ and $\hat{y}_{it} - \hat{y}_i = (x_{it} - \bar{x}_i)'\,\hat{\beta}$ (Hauser,2019). With regards to ROA, R^2(within) shows a 31% variation within one traditional banks over time and a 70% variation within one fintech over time. R^2(between) shows 36% variation between traditional banks and 77% variation between fintechs. R^2(overall) shows 27% for traditional banks and 47% for fintechs. We could find out that fintechs have higher R^2s, which indicate higher variation was presented in fintechs.

	Traditional banks		Fintechs	
	Estimations	Robust Std. Err	Estimations	Robust Std. Err
Intercept	0.183	0.5762	-1.0428	0.6931
Non-performing loan ratio	-2.5889**	1.1084	-3.4581*	2.6408
Net Charge-off rate	-0.0908*	0.4194	-15.7116	7.7032
Total loan loss ratio	-0.0362	0.5319	-5.7916**	1.9401
Value at risk	-0.0005*	0.00037	0.0225*	0.0342
Liquidity coverage ratio	0.0016*	0.0282	0.0008	0.4380
Current ratio	0.6613	0.5327	0.1244**	0.0850
Tier 1 capital ratio	0.1716***	0.5339	0.2293*	0.2826
Debt-to Asset ratio	-0.514**	0.1869	-3.6079***	0.5685
Debt-to-Equity ratio	-0.0097**	0.0116	0.0449*	0.0386
Brand value change %	0.0336	0.0547	0.0628	0.0582
Operational risk %	-0.0465*	0.2307	-0.0036	0.4345
Ln(Asset)	-0.0014***	0.0079	0.4367***	0.1036
Cost-to-Income ratio	-0.2286**	0.1162	-0.0328**	0.0943
R^2_{within}	0.3547		0.7032	
$R^2_{between}$	0.4218		0.7809	
$R^2_{overall}$	0.2941		0.4017	
No. of Obs.	99		58	

Table 4.10 Random-effects estimation results (ROE, China)

Note: *, **, ***represent significance at the 10%, 5% and 1% levels respectively.

Besides ROA, ROE also shows consistent results through random-effects panel data regression estimations in Table 4.9. For traditional banks, this study exhibits some similar results to previous studies. For example, we see the significant and negative effects of NPL on ROE which is the same as Zhang et al. (2015). We also see a significant positive effect of LCR on ROE which is consistent with Zhang (2011). As with Pinto & Joseph (2017) and Siddik, Kabiraj, & Joghee (2017), we see a significant negative effect of D/E on ROE. Besides confirming the previous studies' results, estimations also showed NCO, ORP, C/I and ln(asset) have a significant negative effect on ROE which suggests that traditional banks need to reduce these risks as observed before in Table 4.9.

In more detail, all credit risk variables negatively impact the ROE, where they have higher coefficient values for the fintechs. This confirms that credit risk hurts ROE performance as shown for ROA. Fintechs should be more concerned about these credit risk variables, as they show a larger impact value. With regards to significance level, NPL and NCO are significant at the 5% and 10% level for traditional banks, while NPL and LoanR are significant at the 10% and 5% level for fintechs. With regards to coefficient values, NPL has the largest coefficient value for traditional banks, a 1% increase in NPL will lead to a 2.589% decrease in Chinese traditional banks' ROE. This suggests that managers should pay more attention to NPL during credit risk management, as NPL not only significantly influences both ROA and ROE, but also has a higher coefficient value. For fintechs, NCO has the largest coefficient number, a 1% change of the NCO will lead to a 15.71% decrease in Chinese fintechs ROE, even though it is not significant, managers still need to keep it low. However, managers should be concerned more with LoanR, as it shows the highest significance level with a relatively high coefficient value.

Next, with regards to market risk, unlike VaR in ROA, it shows different results based on types of bank. VaR has a significantly negative impact on traditional banks' ROE at the 10% significance level. A 1% increase in VaR will lead to a 0.0005 decrease in traditional banks' ROE. Thus, to increase the bank's ROE, managers should keep the VaR relatively low. However, at the 10% significance level, a 1% increase in VaR will lead to a 0.0225% increase in fintechs' ROE. As VaR show a different impact on bank performance, managers should take more care about market risk with its complexity.

Thirdly, with regards to liquidity and capital risk variables, similar to ROA, all three variables positively impact the ROE. For traditional banks, LCR and T1 are significant at the 10% and 1% level. This suggests that increased tier one capital and liquidity holding percentages in the traditional banks would improve their equity performance. A higher significance level for T1 suggests that managers should pay more attention to ensure T1 meets the requirement. For fintechs, CR and T1 are significant at the 5% and 10% level. This suggests that increased current ratio and tier one capital holding percentage cwould improve fintechs' ROE. With regards to coefficient values, CR shows the highest value for traditional banks. Even though the CR is not significant in the ROE model, with a higher coefficient value, managers should keep the CR of a healthy level, which could help them achieve a better ROE. For fintechs, T1 shows the highest coefficient value, a 1% increase in T1 will lead to a 0.02293% increase in ROE. Based on its significance level and coefficient value, managers should focus more on fintechs' T1. Moreover, even though the LCR does not have significant impact on the ROE, it is not said that LCR is not essential; fintechs still need to follow the legal requirements. Regarding the debt level, both D/A and D/E negatively and significantly impact ROE at the 5% significance level for traditional banks, which suggests that a decreased debt level in traditional banks would increase their ROE performance. For fintechs, when concerning debt level variables, D/E is important. It is not significant in ROA with a negative impact, but is significant in ROE with a positive impact. The reason could be that during the investigating time, negative D/E existed in Chinese fintechs. Even with the positive sign, this will hurt performance. Moreover, as D/A still negatively impacts ROE at the 1% significance level, managers should be more concerned with D/A than D/E when managing debt level risk variables and keep the debt at an acceptable level. In the future, data should be recollected for fintechs. With a more extended time period than in this research, we could see if the results will change or not with the development of these fintechs.

With regards to reputational risks, similar to the results obtained from ROA, BVC positively impacts on ROE for both types of bank. This means that increase brand value and bank size could help Australian banks to improve their performance. With larger coefficient values, fintechs could receive higher impact with increase in ROE.

Moreover, ln(asset) shows similar results with ROA. It negatively impact traditional banks' ROE but positively impact fintechs' ROE. The result suggests that maintaining or decreasing the safety amount of assets could help traditional banks perform better in ROE. But for fintechs, increasing size tends to have a higher ROE.

Finally, concerning operational risk variables, both variables have negative impacts on ROE for both types of banks. This suggests that Chinese banks should keep operational risk variables low, which could help banks achieve a better ROE. Based on significance levels and coefficient values, managers should consider more on particular operational risks for traditional banks. Fintechs need to control their overall costs and increase their operational efficiency. Overall, the coefficient values in ROE are around ten times larger than coefficient values in ROA. The possible reason could be that the ROE values are around ten time larger than ROA. Unlike traditional banks, fintechs' ROE coefficient values do not show ten times larger than fintechs' ROA coefficient values. The possible reason could be that their ROA and ROE are not stable as they still in developing stage. When they run long enough, the results may tend similar to traditional banks.

Similar to ROA, we looked the R^2 for our ROE models. R^2(within) shows a 35% variation within one traditional banks over time and a 70% variation within one fintech over time. R^2(between) shows 42% variation between traditional banks and 78% variation between fintechs. R^2(overall) shows 29% for traditional banks and 40% for fintechs. We could find out that fintechs have higher R^2s, which indicate higher variation was presented in fintechs.

	Traditional banks		Fintechs	
	Estimations	Robust Std. Err	Estimations	Robust Std. Err
Intercept	0.0594	0.5577	-0.6954	0.5371
Non-performing loan ratio	-0.7150*	0.5802	-8.2467**	6.7153
Net Charge-off rate	-0.1468*	0.2201	-10.9282**	9.1406
Total loan loss ratio	-0.0558	0.2852	-4.1195*	6.5968
Value at risk	-0.0006***	0.0002	-0.0305***	0.0224
Liquidity coverage ratio	0.0104*	0.0147	0.0013**	0.0194
Current ratio	0.5348*	0.5309	0.0294	0.1017
Tier 1 capital ratio	0.3032	0.2864	1.9447**	2.0570
Debt-to Asset ratio	-0.0439*	0.1032	-0.1459	0.5201
Debt-to-Equity ratio	-0.0004	0.0062	0.0001**	0.0217
Brand value change %	0.0105**	0.0296	0.0255	0.1160
Operational risk %	-0.0909*	0.1329	-2.1017**	2.2866
Ln(Asset)	-0.0047***	0.0051	0.0970**	0.1265
Cost-to-Income ratio	-0.027***	0.0596	-0.2015*	0.1997
R^2_{within}	0.3230		0.6012	
$R^2_{between}$	0.3681		0.6292	
$R^2_{overall}$	0.2062		0.5228	
No. of Obs.	99		30	

Table 4.11 Random-effects estimation results (EPS, China)

Note: *, **, ***represent significance at the 10%, 5% and 1% levels respectively.

Finally, we are interested in observing whether the stock market's bank performance depends on managing different types of risks. The random-effects panel regression models are also applied to estimate coefficients and provide these results with EPS in Table 4.11.

For traditional banks, the findings suggest that the impacts of credit risk are important to the stock market's performance, where NPL and NCO are both significant at the 10% level. This suggests that traditional banks with high credit risk have a higher chance of losing profit on the share market. In the credit risk variables, the NPL has the largest coefficient number, 1% increase of the NPL will lead to 0.715% decrease of the EPS where NCO and LoanR could lead to 0.1468% and 0.0558% representatively. As NPL shows its importance in all three dependent variables, this suggests that managers should concern more on NPL during traditional banks' operations. With regards to market risk, with significant negative influence, the higher market risk of traditional banks is shown by the worse EPS of traditional banks. Based on VaR's negative influence on all three dependent variables, traditional banks should keep their VaR relatively low and stable, which could help them perform better.

With regards to liquidity and capital risk variables, similar to ROA and ROE, LCR has significant and positive effects on EPS. It is significant for all three dependent variables, which suggests that managers should pay more attention to LCR to meet the legal requirement. CR and T1 also provide a positive relationship with EPS, where CR is significant at the 10% level. In more detail, a 1% change in LCR will lead to 0.0104% positive change of EPS, where CR shows 0.5348%, and T1 shows 0.3032% positive changes to EPS. Even though they are not significant for all three dependent variables, the result indicates enough liquidity and capital holding percentage will help banks receive better performance with their relatively high coefficient values. Similar to Siddik, Kabiraj, & Joghee, (2017), D/A has significant and negative effects on EPS which is the same as for ROE. The results suggest that traditional banks should keep a healthy liquidity level and reduce their debt level, which will improve their overall performance.

For reputational risks, the BVC has a significant and positive effect on EPS at 5% significance level, indicating that traditional banks with a better reputation could perform better on the share market where 1% increase in BVC will lead to 0.0105% increase in their EPS. Thus, as BVC shows its positive influence on all three dependent variables and significance to ROA and EPS, Chinese traditional banks should aim to increase their reputation during operations.

With respects to the operational risk variables, both of them show significant and negative impacts on the EPS with a 10% level (ORP) and 1% level (C/I). Thus, by lowering the overall cost and operational penalties in bank income, traditional banks could profit in the share market. C/I shows more influence on EPS with a higher significance level, which suggests that managers should consider more on reducing operational cost. As both variables show significant influence on EPS, decreasing the operational risks could help banks develop their performance, where 1% decrease in ORP and C/I will increase 0.0909% and 0.027% of EPS, respectively. Some previous studies confirm this result. For example, Mathuva (2009) also showed that increased C/I would hurt Kenyan's bank performance.

Moreover, due to the large scale of sample traditional banks' assets, similar to ROA and ROE, ln(asset) of traditional banks shows a significant negative impact on EPS. Thus, for Chinese traditional banks, maintaining a smooth or reducing safe amount of assets could increase their overall performance. However, the negative relationship found in this research is opposite to some previous studies (e.g., Bhattacharyya & Purnanandam, 2011), who suggested that increased bank size could increase the EPS for banks.

Because fintechs are still in developing stage, most of them are not in the stock market. A similar situation happened in our dataset that not all Chinese fintechs are in the share market. We only selected fintechs that had joined the stock market for analysing EPS. The panel data regression model shows that the credit risk influence level is high. For example, all credit risk variables significantly negative effect the EPS with much high estimate value. This shows that credit risk has a more significant impact on fintechs than traditional banks, especially on EPS. In more detail, NPL and NCO present a 5% significance level, and LoanR shows a 10% significance level. Based on coefficient values, 1% increase in NPL, NCO or LoanR will lead to 8.2467%, 10.9282% and 4.1195%, respectively. For market risk variables, VaR also has a negative impact in a 1% significance level, which proves the higher market risks are, the worse fintechs perform. A 1% increase of VaR will lead to 0.0006% decrease in EPS.

With regard to liquidity and capital risks, with higher liquidity and capital hold, there is more chance for fintechs to receive higher EPS. With a 5% significance level showed in LCR and T1, managers in fintechs should keep monitoring these variables and following the legal requirements, which could help fintechs increase their EPS. In more detail, a 1% change in LCR will lead to 0.0013% positive change of EPS, where CR shows 0.0294%, and T1 shows 1.9447% positive changes to EPS. Concerning debt level, similar to ROE, D/E has 5% significantly positive impact, where a 1% change in

D/E will lead to 0.0001% negative change in EPS. This shows that with negative equity, reduced debt will help increase EPS. D/A, on the other hand, like ROA and ROE, shows a negative impact on EPS. Thus, Chinese fintechs need to reduce the debt level, and similar to ROE, with the equity situation of fintechs becoming better in the future, the estimations should be rerun for a better fit.

Similar to results shown in ROA and ROE, consistent results were found with respect to operational risk variables in EPS. Both of them significantly and negatively affect the EPS, where a 1% change in ORP will lead to 2.1017% negative change and C/I shows 0.2015% negative impacts. This suggests that reducing operational risks with more focus on ORP could help fintechs increase in the EPS performance. For reputational risks, consistent results are presented. BVC shows its positive impact on fintechs' EPS, where a 1% increase in BVC will lead to 0.0255% increase in their EPS. So, similar to ROA and ROE, managers should increase fintechs' BVC during operations which could help them increase their performance.

At last, fintechs size (ln(asset)) has a positive and significant relationship with EPS at 5% significance level, where 1% increase in ln(asset) will lead to 0.097% of the increase in EPS. Because ln(asset) has a significant positive influence on bank performance for fintechs and significant negative influence on bank performance for traditional banks, these results indicate that larger size could increase bank performance to a certain level. After that, it would decrease bank performance. This confirms the findings of some previous studies (e.g. Athanasoglou et al., 2008 and Berger & Humphrey, 1994).

Similar to ROA and ROE, we looked the R^2 for our EPS model. R^2(within) shows a 32% variation within one traditional banks over time and a 60% variation within one fintech over time. R^2(between) shows 36% variation between traditional banks and 63% variation between fintechs. R^2(overall) shows 21% for traditional banks and 52% for fintechs. We could find out that fintechs have higher R^2s, which indicate higher variation was presented in fintechs.

In summary, the results show consistent results between types of bank. Firstly, all credit risk variables showed a negative influence on bank performance. This suggests that reducing credit risks could help both types of banks increase their performance. Secondly, LCR, CR and T1 showed a positive influence on bank performance. Thus, both types of banks should follow legal requirements to increase their liquidity and capital holding level, which could help them perform better. Thirdly, operational risk variables showed a negative influence on bank performance. It suggests that for both types of banks, controlling operational issues and costs could increase their performance. Finally, developing the bank's reputation could help both types of banks increase their performance. Therefore, for both traditional banks and fintechs, a better reputation, healthy liquidity conditions, efficient credit risk management, lower debt and cost levels and alertness to market movement could provide better performance in both returns and on the stock market.

Besides similarities, four differences exist between traditional banks and fintechs that can be seen through the regression estimations. The first difference is shown in credit risk. It shows a higher level of impact on fintechs than traditional banks with higher coefficient value of estimates. One possible reason could be that consumers quantity, loyalty, and quality are lower than for traditional banks. As fintechs' develop, the results should improve. The second difference is market risk. For fintechs, it shows a higher level of impact and is significant in the regressions for all three dependent variables. It suggests that fintechs should be ready to react to market risk. For traditional banks, the market risk might be less worrisome because there are fewer impacts of the recent financial crisis, and the Chinese government is more involved in stabilising the market than in other countries.

The third difference is the size of the ln(asset). It has a positive influence on fintechs but a slightly negative impact on traditional banks. As traditional banks have been established for a long time and have reached a substantial level of assets, maintaining the safe level or reducing useless assets could help them perform better. However, the higher level of assets owned by fintechs, the better performance will be. The last difference concerns operational risk. For traditional banks, ORP shows significance across the three dependent variables which means traditional banks need to avoid particular operational issues occurring. However, for fintechs, C/I is significant for all three dependent variables, which means that fintechs should monitor the overall cost of their operations at the developing stage. With increasing the operational efficiency, the performance of operational risk will also improve.

In addition, in order to have a more comprehensive view, as noted in Chapter 3, a dummy variable (SOB) could be added in the panel data regression models. The detailed analysis can be found in Appendix 1. In summary, the results are consistent compared with the results obtained above. With regards to the dummy variable (SOB), it shows a positive impact on all three bank performance variables. It suggests that state-owned banks enjoyed more scale efficiency than other banks. However, SOB is only significant for ROA and ROE, which indicates that being a state-owned bank has more impacts on performance for assets and equity but not on stock market performance. Moreover, with the highest estimate value, the SOB influences ROE more than the other two dependent variables.

4.2.7 GMM estimates for China

In addition to the random-effect model, we can use GMM to check if our results from the random-effects model are robust. According to Anderson and Hsiao (1981), Arellano and Bond (1991), and Blundell and Bond (1998), the GMM is a powerful tool in econometrics. GMM could solve unobservable heterogeneity caused by endogeneity and simultaneity of the variables (Wintoki et al., 2012). Thus, even though we called GMM a robustness check for our random-effects models, the results from the GMM are as important as we got from the random-effects models. We will use and compare both approaches' results (Random-effects and GMM) to build our discussion and conclusions.

Similar to Athanasoglou et al. (2008) and Tan (2016), the model of GMM can be expressed as $y_{it} = \beta_0 + \delta y_{i,t-1} + \sum_{j=1}^{k} \beta_j x_{jit} + u_{it}$, where y represent the performance variables; x represents the risk variables and bank size; β_0 represents the constant term; $y_{i,t-1}$ is one period lagged performance variables; δ is the speed of adjustment to equilibrium; $\beta_j\ (j = 1, \dots, k)$ are coefficients to be estimated; i and t are indices for the sections and time, respectively; $u_{it} = \alpha_i + \varepsilon_{it}$, where α_i is the bank-specific unobserved effect and ε_{it} is the error term. Tables 4.12 to 4.14 report the GMM estimates for the impacts of risks on the bank performance (ROA, ROE and EPS, respectively) in China.

	Estimations	
	Traditional banks	Fintechs
Intercept	0.1095	-0.5654
One period lag of ROA	0.3299*	0.0236
Non-performing loan ratio	-0.0591*	-2.6789*
Net Charge-off rate	-0.0091	-4.2111**
Total loan loss ratio	-0.0028*	-3.1013**
Value at risk	-0.0001	-0.0008*
Liquidity coverage ratio	0.0009*	0.0056
Current ratio	0.0603	0.0001
Tier 1 capital ratio	0.0062**	0.0432*
Debt-to Asset ratio	-0.0201	-1.2192
Debt-to-Equity ratio	-0.0013*	0.0001
Brand value change %	0.0009***	0.1869***
Operational risk %	-0.0054*	-0.0020***
Ln(Asset)	-0.0076*	0.0743***
Cost-to-Income ratio	-0.0108	-0.0312
F-test	180.9***	2973.4***
Sargan Test (p-value > χ^2)	32.9(0.472)	60.74(0.343)
AR(1)	z = -3.94 p-value = 0.00	z = -34.15 p-value = 0.00
AR(2)	z = -0.24 p-value = 0.82	z = -1.25 p-value = 0.22
No. of Obs.	99	58

Table 4.12 GMM estimation results (ROA, China)

Notes: *, **, ***represent significant at 10%, 5% and 1% respectively.

Sargan test is the test for over-identifying restrictions in GMM dynamic model estimation.

AR(1) and AR(2) are Arellano-Bond test that average autocovariance in residuals of order 1 and 2 is 0 (H_0: no autocorrelation).

Firstly, ROA was selected as the dependent variable to establish two GMM estimates based on bank type. The F-statistics show the significance of the variables, and the Sargan test shows there is no evidence of over-identifying restrictions. As we used the lag order of the dependent variable to be the explanatory variable, it is necessary to test over-identifying problems caused by selecting the lag order dependent variable. Sargan test could do this test, where the null hypothesis is that the restriction of the model on over-identifying is sufficient; and the alternative hypothesis is that the model has over-identifying problems. Thus, a reasonable test should not reject the null hypothesis. As the Sargan test follows a χ^2 distribution, we checked and found out the Sargan test value cannot be rejected in our model. Furthermore, based on Arellano and Bond (1991), the inconsistency would be applied when second-order autocorrelation is presented. In this study, the second-order autocorrelation is rejected by AR(2) errors and even though a negative first-order autocorrelation is presented, the estimates of independent variables are still consistent.

For Chinese traditional banks, the significant coefficient of the lagged ROA confirms the dynamic character of the model specification. Based on Athanasoglou et al. (2008), a value of δ close to 0 represents a competitive structure, and a value close to 1 represents a less competitive structure. δ takes a value of 0.33 when ROA measures the bank performance. This result suggests that traditional Chinese banks' performance seems to persist and implies that traditional Chinese banks may not be too far from a perfectly competitive market structure.

Turning to the other independent variables, the results here for the dependent variables are consistent with our random-effect panel data regression models. Firstly, credit risk variables have negative impacts. This suggests that higher credit risks lead to poor performance for Chinese traditional banks. In details, NPL and LoanR also significantly negative impact the ROA at the 10% level. In these credit risk variables, the NPL has the largest coefficient number, 1% change of the NPL will lead to 0.0591% of the ROA where NCO and LoanR could lead to 0.0091% and 0.0028% representatively. Similar to random-effects models, NPL shows its importance in credit risk management in both significance level and coefficient value. Thus, this suggests that managers should pay more attention to NPL during credit risk management. With regards to market risk variables, VaR has a negative impact on ROA, which is also similar to the results from random-effects estimates. With a relatively low and not significant coefficient value, Chinese traditional banks can worry less about the impact of market risk on ROA.

Regarding the capital and liquidity risk variables, consistent results also show in GMM compared with random-effects. LCR and T1 have significant positive impacts on ROA with 10% and 5% respectively. Even though the CR is not significant in the ROA model, with a positive and relatively large coefficient value, managers should keep the CR at a healthy level which could help them achieve a better ROA. The results indicate that following the regulation requirements (e.g. Basel Accords) and increasing the capital holding level could increase their performance. We further notice that the debt level variables are negatively related to bank performance, where D/E is significant for ROA at the 10% level. Same to D/E, D/A negatively impacts the ROA for traditional banks with stronger influence with a higher coefficient value. Similar to the results from random-effects, the GMM results suggest that a lower debt level could help banks to receive better performance.

With regards to operational risk variables, GMM also provides results consistent with our random-effects panel data regression models. Both variables affect ROA negatively with a higher risk level, where ORP is significant at the 10% level. Based on the coefficient values, a 1% increase of ORP or C/I will lead to 0.0054% or 0.0108% of changes in ROA. Even though changes in C/I will change ROA more, the higher significance level of ORP suggests that with a relatively developed operational risk management system, managers in Chinese traditional banks should be concerned more with particular operational risks instead of general operational costs.

For reputational risk variables, BVC shows a significant positive impact to ROA at 1% significance level, where a 1% increase in BVC will lead to 0.0009% increase in their ROA. This suggests increasing in reputation could help the banks increase ROA performance. Finally, the bank size coefficient is significant and negatively impacts bank performance at the 10% significant level for ROA. This result is consistent with

Tan (2016), who also found a negative relationship between the size of Chinese traditional banks and performance.

For Chinese fintechs, The F-statistics show the significance of the variables. The Sargan test shows there is no evidence of over-identifying restrictions. The AR tests show that the estimates of independent variables are consistent. With regard to lagged dependent variables, although it is not significant, the coefficient of the lagged ROA shows the dynamic character of the model specification. δ takes a value of approximately 0.024, which suggests that the performance of the Chinese fintechs seems to persist to a perfectly competitive market structure in ROA.

Estimates for the independent variables show results for ROA consistent with our random-effects panel data regression models. Firstly, all credit risk variables have negative impacts and the coefficient values of these variables are larger than were obtained for traditional banks. Moreover, all three variables significantly negatively impact the ROA, where NPL has a 10% significance level, NCO and LoanR have 5% significance level. In more detail, a 1% increase in NPL will lead to 2.68% decrease in ROA, NCO shows 4.21% and LoanR shows 3.1%. This confirms that credit risk hurts bank performance as in traditional banks, but that fintechs should be even more concerned with these credit risk variables. With regards to market risks, VaR shows a negative relationship with bank performance and is significant at the 10% level for ROA. In addition, as fintechs are more related to other markets and have a smaller market scale than Chinese traditional banks. Thus, they should take more care about market risks with their relatively weak market position in the financial system.

With regards to the capital and liquidity risk variables, similar results are presented compared with results from random-effects models. Fintechs with a higher level of capital and liquidity holdings level and meet legal requirements for these variables could obtain better performance. In more detail, slightly different results are shown in these variables. All of them positively impact the ROA, but only T1 has a 10% significantly positive impact, but not like shown in random-effects estimates where CR is significant. Based on coefficient values, a 1% increase in CR will lead to 0.0001%

positive change of ROA, where LCR shows 0.0056% and T1 shows 0.0432% positive changes to ROA. With regards to debt variables, the results show that D/A has a negative impact where D/E has a positive impact on ROA. This result is consistent with our random-effects panel data regression models, which also presents the same results that D/E has the opposite effect on ROA compared with traditional banks' results. Compared with the Chinese traditional banks, the possible reason for this result could be because negative values of D/E exist in Chinese fintechs. Even with the positive sign, D/E ratio will hurt performance. Thus, data should be recollected in the future for fintechs to have a more extended time period than in this research, and the results may change with the development of these fintechs. Thus, the importance of D/A is seen, which is proved by the higher coefficient value. This suggests that managers should consider more on D/A when managing risks.

With regards to operational risk variables, both variables also show negative impact on ROA, where 1% change in ORP will lead to 0.002% negative impact and C/I shows 0.0312% negative impact. With the significance level, the ORP shows a 1% significance level. Unlike GMM estimates shown in traditional banks, together with control over particular operational risks, Chinese fintechs also need to control their overall costs and increase their operational efficiency to obtain better performance. With regards to reputational risk variables, consistent results are shown compared with random-effects estimates for Chinese fintechs and GMM estimates for Chinese traditional banks. BVC also shows a significant positive impact on ROA at the 1% significance level which suggests that increased reputation could help fintechs achieve better performance. Finally, similar to the random-effects estimates for ROA, there is evidence of a positive relationship between size and ROA performance. At 1% of significance level, a 1% increase of fintechs' ln(asset) will lead to a 0.0743% increase of fintechs' ROA, which suggests that increasing size tends to result in better performance.

	Estimations	
	Traditional banks	Fintechs
Intercept	0.2911	-0.2039
One period lag of ROE	0.5231***	0.2428
Non-performing loan ratio	-0.1863***	-1.3283*
Net Charge-off rate	-0.2352*	-1.2324
Total loan loss ratio	-0.2005	-1.1668*
Value at risk	-0.0004**	-0.0041
Liquidity coverage ratio	0.0172*	0.1870***
Current ratio	0.2266	0.0019*
Tier 1 capital ratio	0.5801*	0.2545
Debt-to Asset ratio	-0.4235**	-0.6280*
Debt-to-Equity ratio	-0.0283	0.0008
Brand value change %	0.0121	0.1028***
Operational risk %	-0.0393**	-0.0095***
Ln(Asset)	-0.0363*	0.3035***
Cost-to-Income ratio	-0.1359	-0.0116*
F-test	280.1***	929.3***
Sargan Test (p-value > χ^2)	24.71(0.851)	41.24(0.942)
AR(1)	z = - 3.88 p-value = 0.00	z = - 36.95 p-value = 0.00
AR(2)	z = -0.82 p-value = 0.42	z = -1.11 p-value = 0.26
No. of Obs.	99	58

Table 4.13 GMM estimation results (ROE, China)

Notes: *, **, ***represent significant at 10%, 5% and 1% respectively.

Sargan test is the test for over-identifying restrictions in GMM dynamic model estimation.

AR(1) and AR(2) are Arellano-Bond test that average autocovariance in residuals of order 1 and 2 is 0 (H_0: no autocorrelation).

Besides ROA, GMM estimates for ROE also show consistent results compared with random-effects panel data regression estimations in Table 4.12. For traditional banks, similar to GMM for traditional banks in ROA, the F-statistics show the significance of the variables. The Sargan test shows there is no evidence of over-identifying restrictions. The AR tests show that the estimates of independent variables are consistent. For the lagged dependent variable, the significant coefficient of the lagged ROE confirms the dynamic character of the model specification. δ takes a value of 0.52 when performance is measured by ROE. This result also suggests that the performance of Chinese traditional banks seems to persist to a moderate extent.

Turning to the other independent variables, the results here for the dependent variables are consistent with our random-effect panel data regression models. Firstly, credit risk variables have negative impacts. This suggests that higher credit risks lead to poor ROE for Chinese traditional banks. In details, NPL and NCO also significantly negatively impact the ROE at the 1% and 10% level. In these credit risk variables, the NCO has the largest coefficient number, 1% change of the NCO will lead to 0.2352% of the ROE where NPL and LoanR could lead to 0.1863% and 0.2005% representatively. Similar to random-effects models, NPL shows its importance in credit risk management based on the highest significance level. With regards to market risk variables, VaR has a significant negative impact on ROE at the 5% significance level, which shows a more significance estimate compared to the results from random-effects estimates. Thus, in order to increase the bank's ROE, managers should control the VaR at a relatively low level.

Regarding the capital and liquidity risk variables, consistent results also show in GMM compared with random-effects. LCR and T1 have significant positive impacts on ROE with a 10% significance level. Even though the CR does not appear significant in the ROE model, with its positive influence, managers should keep the CR in a health level which could help them to achieve a better ROE. The results indicate that following the regulation requirements (e.g. Basel Accords) and increasing the capital holding level could help banks increase their performance. We further notice that the debt level variables are negatively related to bank performance, where D/A shows its significance for ROE at the 5% level. In more detail, a 1% decrease in D/A will lead to 0.4235% increase in ROE where D/E shows 0.0283% influence in ROE. Similar to the results from random-effects, the GMM results suggest that a lower debt level could help banks to receive better performance.

With regards to operational risk variables, GMM also provides results consistent with our random-effects panel data regression models. Both variables affect ROE negatively, where ORP is significant at the 5% level. Based on the coefficient values, a 1% increase of ORP or C/I will lead to 0.0393% or 0.1359% of changes in ROE. Similar to the

GMM for ROA in traditional banks, even though changes in C/I will changes ROE more, the higher significance level of ORP suggests that with a relatively developed operational risk management system, managers in Chinese traditional banks should be concerned more with particular operational risks instead of general costs of operations.

For reputational risk variables, BVC shows a positive impact on ROE, where a 1% increase in BVC will lead to 0.0121% increase in their ROE. This suggests that increasing in reputation could help banks increase ROE performance. Finally, the coefficient for bank size is significant and negatively impacts on bank performance at the 10% significant level for ROE. This result is consistent with Tan (2016), who also found a negative relationship between the size of Chinese traditional banks and performance. Overall, similar to random-effects estimates, the coefficient values of ROE are around ten times larger than coefficient values in ROA. The possible reason could be that the ROE values are around ten times larger than ROA. The GMM further confirmed this result.

For Chinese fintechs, The F-statistics show the significance of the variables. The Sargan test shows there is no evidence of over-identifying restrictions. The AR tests show that the estimates of independent variables are consistent. With regard to lagged dependent variables, although it is not significant, the coefficient of the lagged ROE shows the dynamic character of the model specification. δ takes a value of approximately 0.2428, which suggests that the performance of the Chinese fintechs seems to near to a perfectly competitive market structure in ROE.

Estimates for the independent variables show results for ROE consistent with our random-effects panel data regression models. Firstly, all credit risk variables have negative impacts and the coefficient values of these variables are larger than were obtained for traditional banks. Moreover, NPL and LoanR have a significantly negative impact the ROE at the 10% significance level. For coefficient values, a 1% increase in NPL will lead to 1.3283% decrease in ROE, NCO shows 1.2324% and LoanR shows 1.1668%. We could see that the coefficient values are larger than they showed in traditional banks like random-effects models. This confirms that credit risk hurts bank performance as in traditional banks, but that fintechs should be more concerned with these credit risk variables. With regards to market risks, VaR shows a negative relationship with bank performance for ROE, where a 1% decrease in VaR will lead to 0.0041% increase in ROE. In addition, as fintechs are more related to other markets and have a smaller market scale than Chinese traditional banks. Thus, they should take more care about market risks with their relatively weak market position in the financial system.

With regards to the capital and liquidity risk variables, similar results are presented compared with results from random-effects models. Fintechs which have a higher level of capital and liquidity holdings level and meet legal requirements for these variables could obtain better performance. In more detail, slightly different results are shown in these variables. All of them are positive impact on ROE, LCR and CR show their positive impact at 1% and 10% significance level. It is not same to show in random-effects estimates where CR and T1 are significant at 5% and 10% significance level. Based on coefficient values, a 1% increase in LCR will lead to 0.187% positive impact on ROE, where CR shows 0.0019% and T1 shows 0.2545% positive impact on ROE. With regards to debt variables, the results show that D/A has a negative impact at a 10% significance level, where D/E has a positive impact on ROE. This result is consistent with our random-effects panel data regression models, which also presents the same results that D/E has the opposite effect on ROE compared with traditional banks' results. The possible reason for this result could be because negative values of D/E exist in Chinese fintechs. Even with the positive sign, D/E ratio will hurt performance. Thus, data should be recollected in the future for fintechs to have a more extended time period than in this research, and the results may change with the development of these fintechs. With the coefficient values, a 1% increase in D/A will lead to 0.628% decrease in ROE, and a 1% increase of D/E will lead to 0.0008% increase in ROE. Thus, the importance of D/A is seen, which is proved by the higher coefficient value. This suggests that managers should consider more on D/A when managing risks.

With regards to operational risk variables, both variables also show significantly negative impacts on ROE, where a 1% increase in ORP will lead to 0.0095% negative change and C/I shows 0.0116% negative impact. With the significance level, the ORP shows a 1% significance level and C/I shows a 10% significance level. Similar to GMM estimates shown in fintechs' ROA, together with control over particular operational risks, Chinese fintechs also need to control their overall costs and increase their operational efficiency to obtain better performance. With regards to reputational risk variables, consistent results are shown compared with random-effects estimates for Chinese fintechs and GMM estimates for Chinese traditional banks. BVC also shows a significant positive impact on ROE at the 1% significance level which suggests that increased reputation could help fintechs achieve better performance. Finally, similar to the random-effects estimates for ROE, there is evidence of a positive relationship between size and ROE performance. At 1% of significance level, a 1% increase of fintechs' ln(asset) will lead to 0.3035% increase of fintechs' ROE, which suggests that increasing size tends to result in better performance.

In addition, similar to the results shown in random-effects estimates and unlike traditional banks, fintechs' ROE coefficient values do not show ten times larger than fintechs' ROA coefficient values. The possible reason could be that their ROA and ROE are not stable as they still in developing stage. When they run long enough, the results may tend similar to traditional banks.

	Estimations	
	Traditional banks	Fintechs
Intercept	0.2497	-1.1039
One period lag of EPS	0.0429	0.4680***
Non-performing loan ratio	-0.6868*	-0.3573*
Net Charge-off rate	-0.2724*	-2.2579***
Total loan loss ratio	-0.3424**	-0.9379**
Value at risk	-0.0009***	-0.0105*
Liquidity coverage ratio	0.0034	0.2195*
Current ratio	0.4973*	0.2661**
Tier 1 capital ratio	0.0552**	0.4510
Debt-to Asset ratio	-0.0949*	-0.2528*
Debt-to-Equity ratio	-0.0038	0.0245*
Brand value change %	0.0171**	0.0083
Operational risk %	-0.0899*	-0.1432*
Ln(Asset)	-0.0038**	0.1766**
Cost-to-Income ratio	-0.1439*	-0.2569*
F-test	224.7***	1437.2***
Sargan Test (p-value > χ^2)	29.14 (0.66)	53.7 (0.60)
AR(1)	z = -2.03 p-value = 0.00	z = -30.13 p-value = 0.00
AR(2)	z = -1.01 p-value = 0.31	z = -1.23 p-value = 0.22
No. of Obs.	99	30

Table 4.14 GMM estimation results (EPS, China)

Notes: *, **, ***represent significant at 10%, 5% and 1% respectively.

Sargan test is the test for over-identifying restrictions in GMM dynamic model estimation.

AR(1) and AR(2) are Arellano-Bond test that average autocovariance in residuals of order 1 and 2 is 0 (H_0: no autocorrelation).

Finally, we are interested in observing whether the stock market's bank performance depends on managing different types of risks. The GMM estimates are applied to show coefficients and provide these results with EPS in Table 4.14.

For traditional banks, similar to GMM for traditional banks in ROA and ROE, the F-statistics show the significance of the variables, the Sargan test shows there is no evidence of over-identifying restrictions, and the AR tests show the estimates of independent variables are consistent. With regard to lagged dependent variables, although it is not significant, the coefficient of the lagged EPS shows the dynamic character of the model specification. δ takes a value of 0.0429 when performance is measured by EPS. This result also suggests that Chinese traditional banks' performance seems to persist in a perfectly competitive market structure in EPS.

Turning to the other independent variables, the results here for the dependent variables are consistent with our random-effect panel data regression models. Firstly, credit risk variables have significant negative impacts. This suggests that higher credit risks lead to poor EPS for Chinese traditional banks. In details, NPL and NCO significantly negatively impact the EPS at the 10% level, and LoanR has the 5% significance level. In these credit risk variables, the NPL has the largest coefficient number, a 1% increase of the NPL will lead to 0.6868% decrease of the EPS where NCO and LoanR could lead to 0.2724% and 0.3424% representatively. Similar to random-effects models, NPL shows its importance in credit risk management based on the highest significance level. With regards to market risk variables, VaR has a significant negative impact on ROE at the 1% significance level which is similar to the results from random-effects estimates. Thus, in oreder to increase the bank's EPS, managers should control the VaR relatively low.

Regarding the capital and liquidity risk variables, consistent results also show in GMM compared with random-effects, that all three variables are positive influence the bank performance. In more detail, slightly different results are shown in these variables. LCR and T1 show their positive impact at 10% and 5% significance level. It is not same to show in random-effects estimates where LCR and CR are significant at the 10% significance level. Based on coefficient values, a 1% increase in LCR will lead to 0.0034% increase of EPS, where CR shows 0.4973% and T1 shows 0.0552% increase of EPS. Even though the LCR does not significant in EPS model, with its positive influence, managers should keep the LCR in a health level and pass the legal requirements, which could help them to achieve a better EPS. The results indicate that following the regulation requirements (e.g. Basel Accords) and increasing the capital holding level could help banks increase their performance. We further notice that the debt level variables are negatively related to bank performance, where D/A is significant for EPS at the 10% level. In more detail, a 1% decrease in D/A will lead to 0.0949% increase in EPS where D/E shows 0.0038% influence in EPS. Similar to the results from random-effects, the GMM results suggest that a lower debt level could help banks to receive better performance.

With regards to operational risk variables, GMM also provides results consistent with our random-effects panel data regression models. Both variables affect EPS significantly and negatively at the 10% level. Based on the coefficient values, a 1% decrease of ORP or C/I will lead to a 0.0899% or 0.1439% increase in EPS. This suggests that Chinese traditional banks should control their operational risks during the business, especially in the stock market. For reputational risk variables, BVC shows a significant positive impact on EPS at the 5% significance level, where a 1% increase in BVC will lead to 0.0171% increase in their EPS. This suggests increasing in reputation could help bank increase EPS performance. Finally, the coefficient for bank size significantly impacts bank performance at the 5% significant level for EPS. With 1% increase in ln(asset), the EPS will decrease 0.0038%.

For Chinese fintechs, The F-statistics show the significance of the variables. The Sargan test shows there is no evidence of over-identifying restrictions. The AR tests show that the estimates of independent variables are consistent. For the lagged dependent variable, the significant coefficient of the lagged EPS confirms the dynamic character of the model specification. δ takes a value of approximately 0.468, which suggests that the performance of the Chinese fintechs seems to persist to a moderate extent in EPS.

Estimates for the independent variables show results for EPS consistent with our random-effects panel data regression models. Firstly, all credit risk variables have negative impacts and the coefficient values of these variables are larger than were obtained for traditional banks. Moreover, all of them are significant where NPL significantly negatively impacts the EPS at the 10% significance level, NCO has a 1% significance level and LoanR has a 5% significance level. For coefficient values, a 1% increase in NPL will lead to 0.3573% decrease in EPS, NCO shows 2.2579% and LoanR shows 0.9379%. We could see that the coefficient values are larger than they showed in traditional banks like random-effects models. This confirms that credit risk hurts bank performance as in traditional banks, but that fintechs should be more concerned with these credit risk variables. With regards to market risks, VaR shows a significantly negative relationship with EPS at 10% level, where a 1% decrease in VaR will lead to a 0.0105% increase in EPS. In addition, as fintechs are more related to other markets and have a smaller market scale than Chinese traditional banks. Thus, they should take more care about market risks with their relatively weak market position in the financial system, especially in the stock market.

With regards to the capital and liquidity risk variables, similar results are presented compared with results from random-effects models. Fintechs which have a higher level of capital and liquidity holdings level and meet legal requirements for these variables could obtain better performance. In more detail, slightly different results are shown in these variables. All of them positively impact the EPS, LCR and CR show their positive impact at 10% and 5% significance level, respectively. It is not same to show in random-effects estimates where LCR and T1 are significant at the 5% level. Based on coefficient values, a 1% increase in LCR will lead to 0.2195% positive change of EPS, where CR shows 0.2661% and T1 shows 0.451% positive changes to EPS. With regards to debt variables, the results show that D/A has a negative impact on EPS at 10% significance level, where D/E has a significant positive impact on EPS at the 10% significance level. This result is consistent with our random-effects panel data regression models, which also presents the same results that D/E has the opposite effect on EPS compared with traditional banks' results. The possible reason for this result could be because negative values of D/E exist in Chinese fintechs. Even with the positive sign, D/E ratio will hurt performance. Thus, data should be recollected in the future for fintechs to have a more extended time period than in this research, and the results may change with the development of these fintechs. With the coefficient values, a 1% increase in D/A will lead to 0.2528% decrease in EPS, and a 1% increase of D/E will lead to 0.0245% increase in EPS. Thus, the importance of D/A is seen, which is proved by its higher coefficient value. This suggests that managers should consider more on D/A when managing debt level risks.

With regards to operational risk variables, both variables also show significantly negative impacts on EPS at the 10% level, where a 1% increase in ORP will lead to a 0.1432% decrease and C/I shows 0.2569% negative impact. Similar to GMM estimates shown in fintechs' ROA and ROE, together with control over particular operational risks, managers also need to control their overall costs and increase their operational efficiency to obtain better performance. With regards to reputational risk variables, consistent results are shown compared with random-effects estimates and GMM estimates for both types of banks, BVC also shows a positive impact on EPS which suggests that increased reputation could help fintechs achieve better performance. Finally, similar to the random-effects estimates for EPS, there is evidence of a positive relationship between size and EPS performance. At 5% of significance level, a 1% increase of fintechs' ln(asset) will lead to a 0.1766% increase of fintechs' EPS, which suggests that increasing size tends to result in better performance.

In summary, the F-statistics confirms the significance of the variables, the Sargan test shows there is no evidence of over-identifying restrictions and the AR tests show the estimates of independent variables are consistent in all our GMM. For Chinese traditional banks, the significant coefficient of the lagged performance variables (ROA and ROE) confirm the dynamic character of the model specification. For Chinese fintechs, the significant coefficient of the lagged performance variable (EPS) confirms the dynamic character of the model specification. These results suggests that the performance of Chinese banks seems to persist to a moderate extent and implies that the Chinese banks may not be too far from a perfectly competitive market structure.

Turning to the other independent variables, the GMM estimations showed consistent results with our random-effects panel data regression models. Firstly, credit risk variables have negative impacts. And with the higher coefficient values for fintechs, the results confirm that credit risk hurts bank performance in both types of banks, but fintechs need to be more concerned with these credit risk variables. Of the three selected credit risk variables, at least two of variables significantly influence the performance, which reflects the importance of credit risk management in banking operations. Moreover, depending on the different performance variables, managers could prioritise credit risk variables and find a balance point to achieve better overall performance. With regards to market risks, VaR shows a negative relationship with bank performance in both types of banks. For traditional banks, the result shows that the influence of VaR related more to the market performance variable and based on its high significance level, managers should consider it more when banks would like a better performance on the stock market. For fintechs, as they are more related to other markets and have a smaller market scale than Chinese traditional banks. Thus, they should take more care about market risks with their relatively weak market position in the financial system.

Next, we find that there is a positive relationship between liquidity and capital holding level and bank performance for both types of bank. The results indicate that following the regulation requirements (e.g. Basel Accords) and increasing the capital holding level could help banks increase their performance. For debt level variables, different results are shown between types. For traditional banks, a lower debt level could help banks to receive better performance. For fintechs, as positive D/E impacts exist for bank performance and negative D/E exists in dataset, fintechs need to balance the debt level and rerun the model with longer investigated time period of investigation.

With regards to operational risk variables, GMM also provides results consistent with our random-effects panel data regression models. The results indicate that with a relatively developed operational risk management system, managers should be concerned more with particular operational risks instead of general costs of operations. For the relatively new established operational risk management system, managers should not only concern with particular operational risk issues like traditional banks but also need to be concerned with overall operational costs. For reputational risk variables, BVC shows a positive impact on all bank performance variables for both types of banks, which means increasing reputation could help bank increase bank performance. With regards to bank size, our results are consistent with our panel data regression models, similar to Athanasoglou et al. (2008), we also showed that bank size shows a positive impact on performance up to a certain level and that size then reduces the performance.

In addition, as mentioned in last section, the same similarities and differences hold in GMM estimates as shown in random-effects panel data regression models. Thus, the GMM reinforced our findings of the impact of risks on Chinese bank performance. Moreover, similar to Appendix 1, a dummy variable (SOB_i) is added for Chinese traditional banks, to show whether ownership influences bank performance. The model becomes $y_{it} = \beta_0 + \delta y_{i,t-1} + \sum_{j=1}^{k} \beta_j x_{jit} + \gamma SOB_i + u_{it}$, and γ is the coefficient of the dummy variable. The estimation results will be shown in Appendix 2.

4.2.8 Summary

This section analysed 22 Chinese banks and listed them as two types (11 traditional banks and 11 fintechs). Firstly, we applied figure comparisons between traditional banks and fintechs. Then, descriptive statistics, stationarity, multicollinearity heteroscedasticity and endogeneity tests were presented and analysed. At last, by using ROA, ROE, and EPS as dependent variables, we employed panel data regression models and GMM to study the impact of different types of risks on different kinds of banks' performances. Moreover, as we used random-effects estimates to build a generalised model for the dataset. We did not need to add time- or individual- influence factors in the analysis, as they already be analysed through R^2.

The overall conclusion for Chinese banks is that improving different bank risk management aspects could help Chinese banks perform better. The reasons for this seem obvious. Due to the recent financial crisis, the BSBC and governments worldwide discovered the importance of risk management. The question is what type of risk needs to be focused on more. Similar to the results shown in Aebi et al. (2012) for the US banking system, this research also proved the importance of risk management for Chinese banking. Consistent with the studies of Geng et al. (2016), Zhang (2011), and Diallo et al. (2015), we also showed the negative influence of credit risk and operational risk, some positive and some negative impact of liquidity and capital risks, and the positive impact of bank brand value on bank performance. We further found that bank size has a slightly negative impact on traditional banks, but a positive impact for fintechs.

According to the empirical findings, for both types of Chinese banks, at least one variable of each type of risk significantly impacted the bank performance in all three different dependent variables. Thus, banks in China should catalogue and prioritise risks through types, then based on our regression analysis, better performance in the future could be achieved. For example, for banks with a long history, sound development and stable performance, more attention should be paid to capital and liquidity risk, than to credit risk, operational risk and market risk. Furthermore, keeping bank size stable and developing bank reputation is important. On the other hand, fintechs established recently and were in the development stage, need to be more concerned about their credit risk, and stay alert to market movements. Also, pay attention to liquidity and capital risk and operational risk at the same time; and then improve their asset level and reputation. Moreover, as differences existing in the significance level and significance between two types of banks, based on the findings in this section, managers of traditional banks and fintechs could use these results to manage different types of risks and use historical data to estimate the future performance. Therefore, managers should be aware of influence level of different types of risks and variables when prioritising these risks. They could further provide a more efficient strategy when managing risks. In addition, managers could estimate their future performance through our models and set risk management targets. For example, based on the historical data, managers can estimate the future values of risk variables for their bank/fintech and receive the performance results based on the bank type. Thus, if the Chinese bank/fintech wants to improve its performance, it can reduce or increase risk variables to achieve the goal. Also, they can set the target value of risk management variables and check in the future if they meet the goal. Moreover, through our models, managers could better understand their competitors, which could help them avoid some mistakes or improve some advantages through management. For example, a bank/fintech can estimate the future risk values for its competitors and get their estimated performance. Then, the manager can compare the results with their performance, finding advantages and disadvantages in risk management. As a result, managers can develop risk management strategies with a more focused risk management target to receive better performance.

At the same time, investors and shareholders in China could also benefit from our models. By finding the relevant variables from banks/fintechs official website or any legal ways, investors and shareholders can receive different results based on the bank type. This could help them know if a bank/fintech develops or which bank/fintech is better to invest in these days. Similarly, policymakers and governments in China could also benefit from our models. Instead of investing in banks/fintechs, they can find banks/fintechs perform better or worse than others which can help them keep their eyes on these banks/fintechs and support or shut down these banks/fintechs. Moreover, through our models, policymakers and governments can understand the general situation for different bank types, which can help them make more targeted regulatory requirements based on bank type. More discussion could be found in Chapter 6.

Based on the processes in this chapter, the following sections consider the UK, Australia and overall datasets. This will allow us to see the differences between countries and types of banks.

4.3 Data analysis, results and discussion for the UK

In the previous section, the risks influencing Chinese banks' performance were identified for traditional banks and challenger banks/fintechs. In order to have a comprehensive result, we will also present results for the UK and Australia following China's same pattern. Similarly to Section 4.2, this section is also organised as follows: 1. Figure comparisons; 2 Descriptive statistics; 3. Panel-data unit-root tests (Fisher's type); 4. Correlation matrix and variance influence factors (VIF); 5. White's test, F-test, Lagrange Multiplier Test and Durbin-Wu-Hausman (DWH) test; 6. Panel data regression models (random-effects type); 7. GMM estimates; 8. Summary.

4.3.1 Comparisons between the UK's traditional banks and fintechs

Figures about bank performance and risk management between the UK's traditional banks and fintechs are presented before presenting the analysis of panel data regression models. Figure 4.8 shows all three performance variables for the UK's traditional banks and fintechs. With regards to ROA, unlike the profitable situation of Chinese traditional banks, the UK's traditional banks mostly stayed in low profits, and some had a loss position during the investigation period. The ROA for the UK traditional banks showed signs of a stable trend but stayed at a low level, except for Barclays. Barclays' performance changed during the investigated time period. Its ROA reached near 6% at 2015H1 and dropped to near -1% at 2017H1. For fintechs, on the other hand, similar to Chinese fintechs, it is easy to verify the growth trend for the UK fintechs. Due to developing in recent years, similar to the UK's traditional banks, the UK's fintechs also had a low-level profit ROA.

A similar trend is seen in ROE for the fintechs. Most of the fintechs started with loss position, then nearly reached to the low-profit position. However, for traditional banks, ROE showed a different situation compared with ROA and Chinese traditional banks' ROE situation. They showed that the 2007-09 financial crisis heavily influenced them. Some of the traditional banks even had negative ROE. Thus, this situation showed that the UK traditional bank performed worse than Chinese traditional banks. However, the ROE showed signs of an increasing trend, which demonstrates good potential for future performance.

For EPS, our figures for both types of banks only show traditional banks/fintechs which already joined the share market. The UK traditional banks had a volatile trend around zero for EPS. The same reasons for this can be applied as for ROA and ROE, which was that the UK was heavily influenced by the financial crisis and a higher level of connections in the share market than China. For fintechs, as only a small amount of them joined the share market, we could not show the whole trend of fintechs. For the sample we have, the develop performance of these samples is shown. Some of them had an extreme loss at the beginning, then the loss reduced. Some of them performed smoothly, which demonstrated their smooth operations during these years. However, because of the lower number of fintechs that joined the stock market, we should wait longer for more fintechs to join the share market, to receive a better view in the future.

In addition, we could see that there are outliers existed for fintechs' performance. Indeed, these points have much lower value than others. This suggests that in the infant stage of fintechs operations, these fintechs could have negative returns or earnings at different levels. If they survived this stage, they could begin to have positive returns and earnings. Therefore, authorities could give fintechs chances even support them pass this stage.

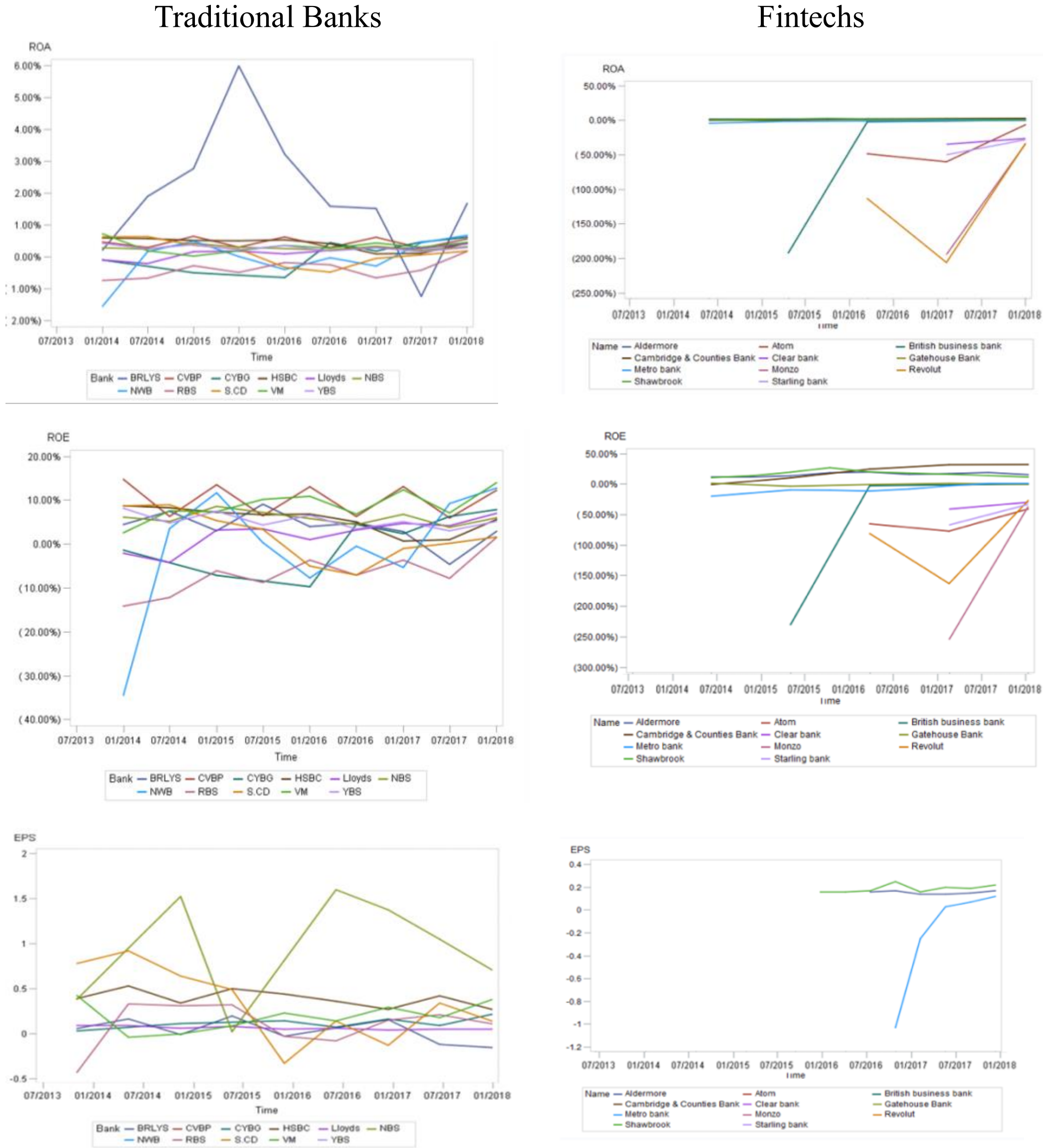
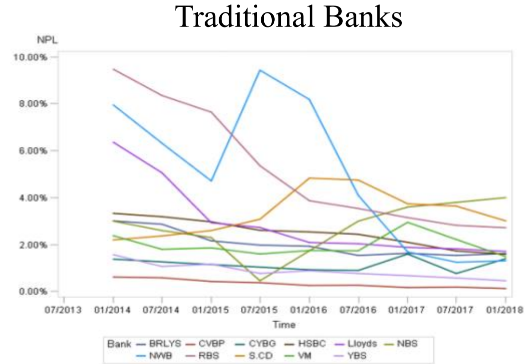


Figure 4.8 Performance comparisons (UK)

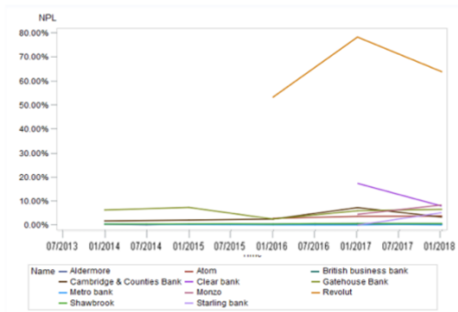
Figures 4.9 to 4.14 present the independent variables, similar to Section 4.2, figures are organised by type of risk. Figure 4.9 presents the credit risk variables. For the UK traditional banks, a decreasing trend was presented during the investigated time period. With a series of regulations and policies that the UK's FCA published after the financial crisis, credit risk management is seen to increase the efficiency of the UK traditional banks. The NPL dropped to near 2%, which neared the NPL of Chinese traditional banks. Similar trends were also seen in NCO and LoanR.

On the other hand, most UK fintechs stayed in a stable range, which was higher than Chinese fintechs but not high enough to endanger the credit business. Moreover, the overall credit risk level of fintechs was shown to be higher than that in traditional banks. In addition, an extreme existed in the UK fintechs, Revolut, which had a higher credit risk level than others. The possible reason should be that it is established very recently where its credit risk management system had not been tested and needed to be improved. The quality of the customers also needs to be improved, which can also help this fintech reduce its credit risks. Moreover, we also need to give this fintech more time to show its management ability and analysable trends of these credit risk variables. Thus, credit risk management of the UK banks was performed worse than Chinese banks. This confirms that the 2007-09 financial crisis had a higher impact on the UK economy. However, traditional banks recovered quickly since then, which suggests a better potential performance of the UK traditional banks, especially in credit risk management.

Traditional Banks



Fintechs



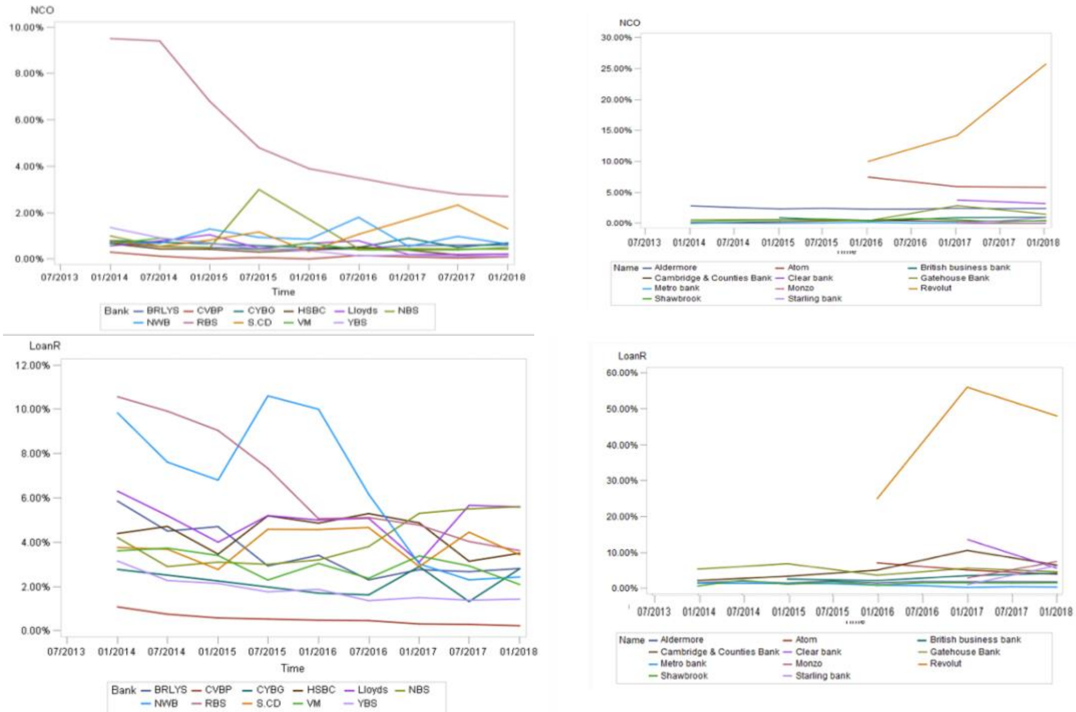


Figure 4.9 Credit risk variables comparisons (UK)

Similar to the credit risk variables, the VaR values of the UK banks were more substantial than the VaR shown in China. The main reasons could be that (1) the global market had a higher impact on and involvement with the UK banks than Chinese banks. (2) GBP had a higher exchange rate against the USD than RMB in the currency value, and so the high value presented was acceptable. In more detail, some of the banks had a stable trend of VaR for both types of banks. Others showed an increasing trend. Thus, for the UK, both traditional banks and fintechs need to be ready to react to the market movement during operations.

Traditional Banks Fintechs

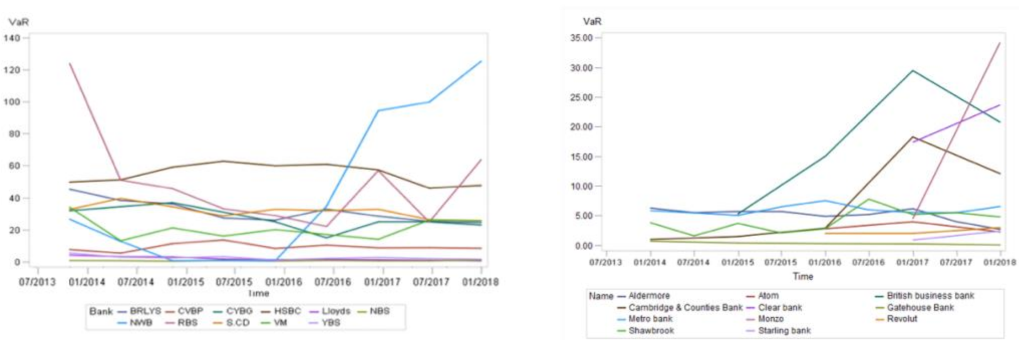


Figure 4.10 Market risk variable comparisons (UK)

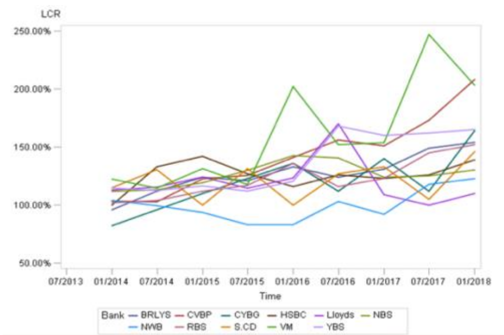
With regards to capital and liquidity risk, in Figure 4.11, we see that both LCR and CR had a similar increasing trend, which showed that the liquidity conditions of the UK traditional banks were well developed. However, some of the UK traditional banks did not meet the 100% LCR requirement after 2015. Similar to China, with warnings, these banks tried to solve this problem. As a result, their LCR increased and met the requirement at the end of 2017. For fintechs, these ratios in most of them did not show a generally increasing trend, while they performed stably at the requirement level. Moreover, some showed a high increasing trend in LCR, which indicates that these fintechs had a better liquidity situation. However, some of them dropped their LCR under 100% after 2015, which suggest a poor liquidity situation for these fintechs to respond to liquidity coverage issues. Thus, these fintechs need to be more concerned about their liquidity situation to prevent serious issues occurring. Moreover, similar to Chinese fintechs, there is an outlier of LCR in the UK fintechs figure (Figure 4.11). With higher values than other fintechs, it can be observed that the outlier shows a high ratio of liquidity to expected cash flow. The possible reason could be that the fintech received many liquidity investments during that period. As the values decrease to the average, it should not be a problem.

With regard to CR, traditional banks show that their CR values were higher than one and had a smoothly increasing trend. However, there are outliers which had higher values for fintechs. For fintechs, most of them had a stable trend and some of them are relatively higher than others. Similar to Chinese fintechs, as the outliers are at the initial years that fintechs published their data, the situation is accepted with a reduced trend with its development.

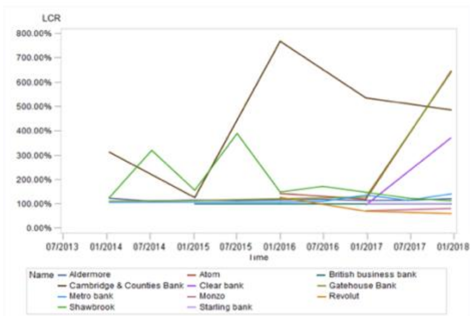
Then, with regards to T1 capital ratio, traditional banks had a healthy capital holding condition (over 10%) which was also higher than the requirement (6%) and higher than Chinese traditional banks (over 8%). The trend of T1 also increased during the investigated time period, which suggests the UK traditional banks had enough tier one capital to prevent bankruptcy. On the other hand, fintechs had a similar trend to traditional banks. This indicates that fintechs had a relatively healthy capital ratio condition during the investigated time period. Moreover, there are outliers in the T1 figure. Similar to Chinese fintechs, the possible reason should be that these fintechs are in their absorbing investment stage. With a high volume of investment in T1 capital, the ratio becomes relatively high. Thus, this situation should be temporary, with their development, T1 would be reduced to the requirement of the banking industry and near the ratio of traditional banks. We should wait and monitor a more extended period for a better view.

With regard to debt level variables, the D/A of the UK traditional banks performed differently between banks, where some of them had a relatively lower level than the others. Thus, for banks with higher D/A values, they should pay more attention to reduce their debt level than the others. The D/E of the UK traditional banks also had a stable trend. Thus, similar to China, the UK traditional banks had a stable trend with respect to the debt level. Fintechs, on the other hand, showed a different situation. Compared with Chinese fintechs, most of the UK fintechs also showed a stable trend in D/A. Similar to China, there is an outlier in D/A figure. As it is in the first year of the fintech published its data, this situation is accepted as the D/A reduced to average with its development. Moreover, there was only one negative value of D/E in the UK fintechs as proposed to several negative values shown in China. This suggests that the UK fintechs control their debt levels better and thus perform better than Chinese fintechs. Even though the high D/E ratio shows the high debt level of fintechs, it is still better than a negative D/E.

Traditional Banks



Fintechs



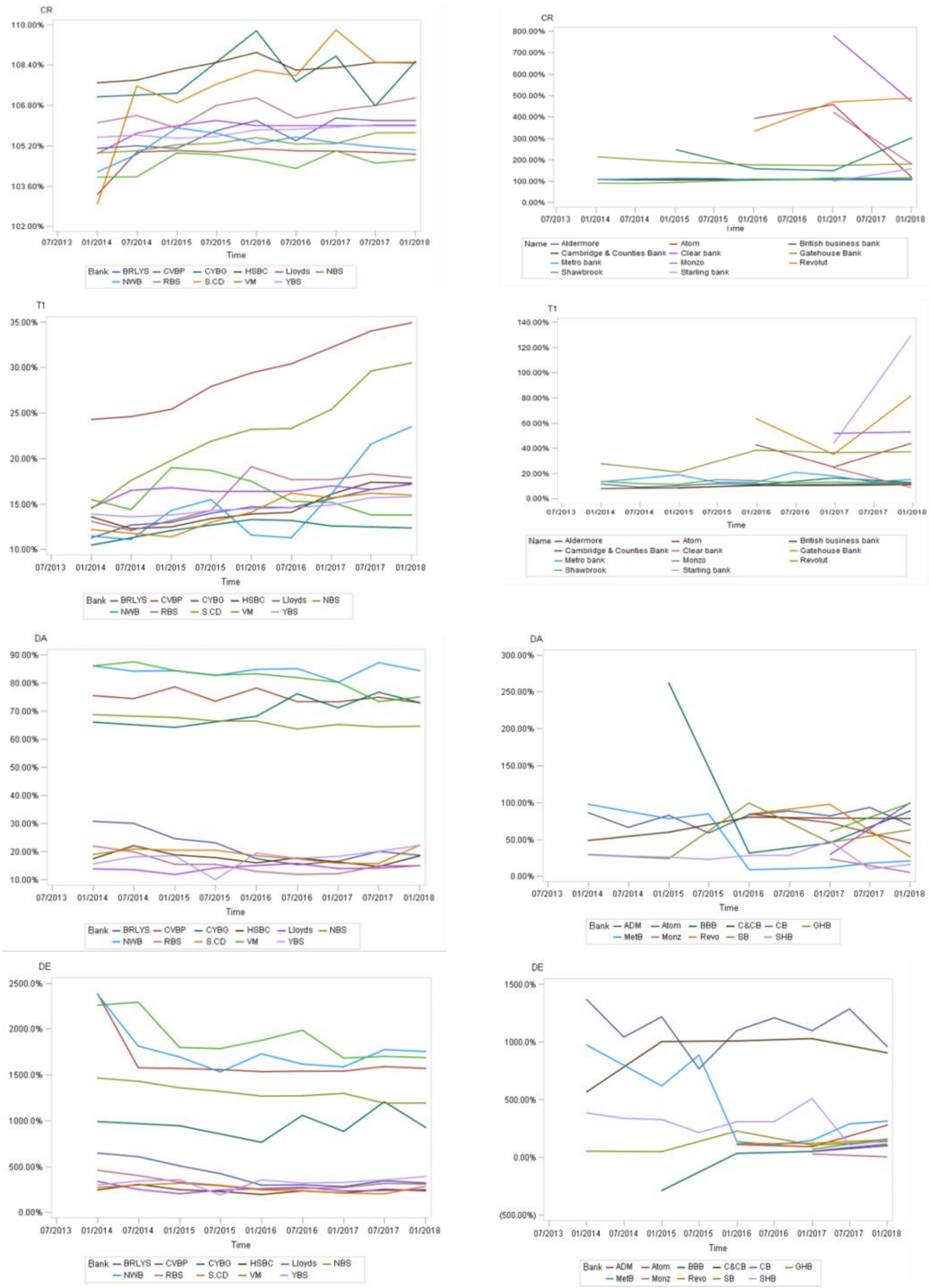


Figure 4.11 Capital and Liquidity risk variables comparisons (UK)

Figure 4.12 presents the reputational risk variable (BVC). For traditional banks, with the influence of the 2007-09 financial crisis, the changes moved around 0%. Thus, the reputation of the UK traditional banks stayed similar during these years. For fintechs, reputation developed during these years. Moreover, it showed a better trend of reputation than it showed Chinese fintechs. However, the trend might not keep developing that well when fintechs step into a mature period. We should give them more time to prove their ability in the financial market.

Traditional Banks Fintechs

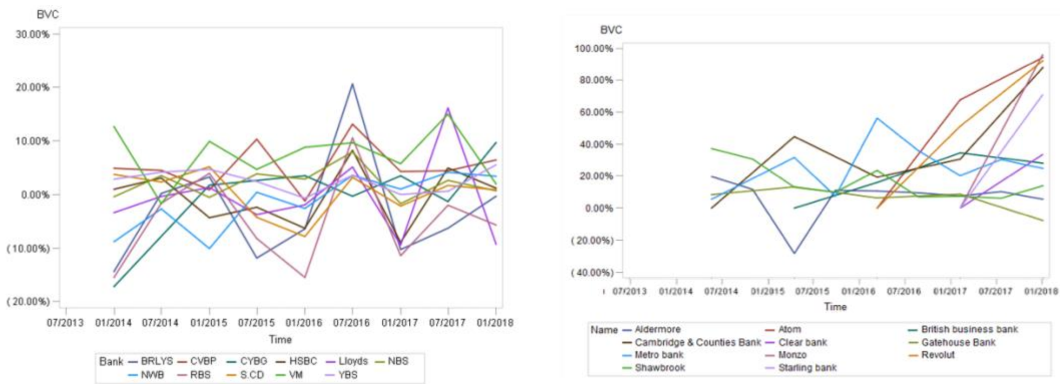


Figure 4.12 Reputational risk variable comparisons (UK)

With regards to the operational risk variables in Figure 4.13, ORP shows a smooth trend for both types of banks, which is similar to the Chinese banks. However, one exception exists for both types of banks, where they provided a much higher ORP than the others and did not meet the Basel III requirement (15%). This suggests that some of the UK traditional banks did not perform as well as Chinese traditional banks. Fintechs, on the other hand, performed similar to Chinese fintechs, as extremes over the limit exist, but others showed an acceptable level.

With regards to C/I, most UK traditional banks kept all their costs less than their income. However, values over than 100% did exist during the investigated time period. Moreover, the maximum C/I for Chinese traditional banks was 38.58% which was much lower than the maximum C/I value in the UK. This result shows that the operational efficiency for the UK traditional banks was much lower than shown in China. Thus, they need to improve their management methods to control costs, including operational risk costs, to better efficiency. For fintechs, some of had costs were higher than incomes, which was a similar situation as shown in Chinese fintechs. This suggests that their operational efficiency was low and needs to improve immediately like Chinese fintechs.

Traditional Banks Fintechs

Figure 4.13 Operational risk variables comparisons (UK)

With regards to bank asset levels (ln(asset)) in Figure 4.14, the UK traditional banks had a stable level which showed that they retained their assets during operations. For fintechs, their asset levels showed signs of a slightly increasing trend which was similar to the Chinese fintechs and better than the UK traditional banks.

Traditional Banks Fintechs

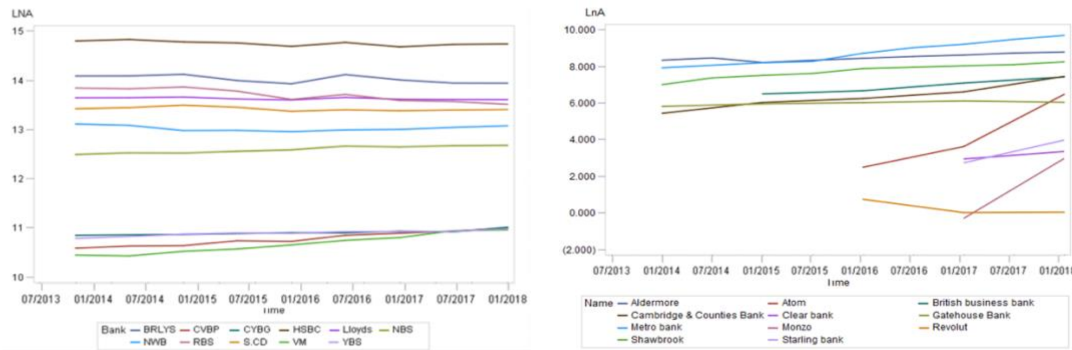


Figure 4.14 Bank size comparison (UK)

In general, the UK traditional banks and fintechs performed at an acceptable level during these years, and they showed their advantages and disadvantages. Therefore, analysing the differences and problems that exist between traditional banks and fintechs could help managers to build better direction and focus for their risk management and future operations.

4.3.2 Descriptive statistics

Tables 4.15 and 4.16 provide descriptive statistics for performance variables and risk variables based on types of bank. With regards to performance, the average ROA value was 0.35% for traditional banks, but -19.23% for fintechs. A similar result was shown for ROE, where the mean value was 3.37% for traditional banks, and -15.37% for fintechs. This confirms the results in Figure 4.8. Both the ROA and ROE of the UK traditional banks had a worse average value than Chinese traditional banks, and the UK fintechs performed worse than the UK traditional banks.

Moreover, even though the UK fintechs did not perform well, they still had a better average value than Chinese fintechs (-39.1%). Concerning EPS, the UK banks performed better on average ($0.3119 for traditional banks and $0.0726 for fintechs) than the Chinese banks, which suggested better market earnings for the UK banks. In summary, the UK traditional banks performed worse than Chinese traditional banks in ROA and ROE but better in EPS. The reasons could be, firstly, the influence of the financial crisis was more substantial in the UK than in China. Secondly, with fewer years' development of China in the stock market, all the Chinese listed companies performed not as well as other countries. The UK fintechs, similar to Chinese fintechs, still need to improve their performance, because they had a negative rate of returns.

In terms of credit risk management variables, the average value of NPL was 2.61% in traditional banks, which also stayed at a low level but higher than the average value of Chinese traditional banks. However, the UK traditional banks performed better for the other two credit risk variables than traditional Chinese banks with a relatively lower average value of NCO and LoanR. Fintechs, on the other hand, had a higher rate than did Chinese fintechs. For example, the average value of NPL was 5.91% which was more than twice the average value of NPL for Chinese fintechs (2.2%). However, the level of credit risk was acceptable with a decreasing trend. Moreover, as a series of support legalisations and tight regulatory requirements about banks were published, the UK fintechs should achieve better in the future.

With regards to VaR, this showed a more substantial risk level for the UK traditional banks than Chinese traditional banks. As the market fluctuated a great deal during the investigating time period, the average value of VaR was 24.87 for the UK traditional banks. Moreover, the standard deviation of VaR was high, which indicates that the market movement had different influence levels for different banks. For the UK fintechs, VaR showed a similar situation to the Chinese fintechs. The average value was 6.2, which was much smaller than that shown in traditional banks. However, with their smaller marketplace and proportions, an even lower VaR might have a significant impact.

Under the liquidity and capital risk variables, the UK traditional banks had a similar situation to the Chinese traditional banks. On average, they showed enough liquidity and capital holding percentages with a reasonable debt level. However, some of the traditional banks performed less well with a lower the LCR (the minimum value is 82.34%). The UK fintechs also showed similar results to Chinese fintechs except for D/E. As noted in the previous section, the UK fintechs had a relatively better situation with respect to D/E level with less negative values. This suggests that the UK fintechs should control their debt level to achieve a better rate.

With regards to BVC, Tables 4.15 and 4.16 confirm the results show in Figure 4.12. Traditional banks increased the limited values of their brand value as their poor performance during the financial crisis, with a 0.7% average value. Fintechs, on the other hand, showed their development in the market with a 23.37% average value. In addition, based on the average value, the bank size of the UK traditional banks was smaller than Chinese traditional banks and the UK fintechs were larger than Chinese fintechs.

With regards to operational risk variables, ORP for the UK banks (traditional banks 12.61% and fintechs 11.38%) showed a higher average value than shown in Chinese banks (traditional banks 2.4% and fintechs 461%, (5.19% without extreme values). This suggests that the UK traditional banks had higher expenses for operational risks than Chinese traditional banks. As the UK traditional banks had a relatively comprehensive operational risk management system to prevent operational risks, the results should be better. The banks with high ORP values should pay more attention during operations to prevent loss caused by occurring operational risks. The UK fintechs performed better than Chinese fintechs, as no extreme issues occurred during the investigated time period. However, as the average value was close to the requirement (15%), the UK fintechs still need to reduce operational risk issues to prevent future disasters. Moreover, C/I showed a lower efficiency of the UK traditional banks where they had a higher average value (66.2%) than Chinese banks (28%). For fintechs, the average value of C/I (4852.4%) had a higher value than was seen showed in Chinese fintechs (137.3%). This shows that the fintechs face a dangerous operational situation and need to cut their operational costs immediately to prevent bankruptcy.

Variable	Mean	Std Dev.	Maximum	Minimum
Return on asset	0.0035	0.0086	0.0598	-0.0154
Return on equity	0.0337	0.0719	0.1476	-0.344
Earnings per share	0.3119	0.4469	1.7909	-0.4300
Non-performing loan ratio	0.0261	0.0202	0.0947	0.0130
Net Charge-off rate	0.0101	0.0160	0.0950	0.0001
Total loan loss ratio	0.0381	0.0228	0.1060	0.0230
Value at risk	24.8742	25.7627	125.5	0.4000
Liquidity coverage ratio	1.2787	0.2718	2.4670	0.8234
Current ratio	1.0611	0.0141	1.0979	1.0290
Tier 1 capital ratio	0.1695	0.0542	0.349	0.1050
Debt-to-Asset ratio	0.4346	0.2952	0.8744	0.1014
Debt-to-Equity ratio	8.5368	6.7258	23.812	1.9228
Brand value change %	0.0070	0.0695	0.2063	-0.172
Operational risk %	0.1261	0.2763	1.9400	0.0041
Ln(Asset)	12.6159	1.1438	14.8300	10.4283
Cost-to-Income ratio	0.6620	0.1955	1.8098	0.3868
Observations			97	

Table 4.15 Descriptive statistics (UK traditional banks)

Variable	Mean	Std Dev.	Maximum	Minimum
Return on asset	-0.1923	0.4936	0.0278	-2.0588
Return on equity	-0.1573	0.5747	0.3201	-2.5458
Earnings per share	0.0726	0.2869	0.25	-1.03
Non-performing loan ratio	0.0591	0.1536	0.7830	0.0002
Net Charge-off rate	0.0220	0.0427	0.257	0
Total loan loss ratio	0.0548	0.1025	0.5600	0.0031
Value at risk	6.5260	7.2428	34.2300	0.0600
Liquidity coverage ratio	1.8075	1.6067	7.6786	0.6000
Current ratio	1.8320	1.4186	7.8128	0.9095
Tier 1 capital ratio	0.2327	0.2187	1.2930	0.0810
Debt-to-Asset ratio	0.5916	0.4149	2.622	0.0554
Debt-to-Equity ratio	4.3293	4.3341	13.6731	-2.85
Brand value change %	0.2337	0.2734	0.9620	-0.2833
Operational risk %	0.1138	0.3767	2.562	0.0003
Ln(Asset)	6.4496	2.6032	9.7010	-0.3010
Cost-to-Income ratio	48.5240	137.0581	600.0000	0.2886
Observations			52	

Table 4.16 Descriptive statistics (UK fintechs)

Notes: Not all UK traditional banks are listed, observations are 70 for EPS.
Not all UK challenger banks/fintechs are listed, observations are 30 for EPS.

Through understanding the descriptive statistics, we conclude that the UK traditional banks' performance and risk management were relatively better than the UK fintechs. However, the BVC of fintechs demonstrated the development of the UK fintechs. Thus, as both of them had advantages and disadvantages, the values of the investigation has been demonstrated.

4.3.3 Panel data unit root test

Similar to China, before applying the regression model, we apply a unit root test for panel data to test the stationarity of the data set at first. In more detail, Fisher-type unit root tests were implemented based on ADF tests to test the stationarity of the data. The null and alternative hypotheses are that H_0 is that the data are non-stationary or have unit roots, and H_1 that the data are stationary or do not have unit roots. The results of the unit root based on bank type are shown in Table 4.17. The results show that all variables are stationary at the 1% level of significance. The null hypothesis for the variables is rejected, indicating that there is no evidence of unit roots and the data are stationary.

	Traditional banks		Challenger banks/fintechs	
Variable	Statistics	P-value	Statistics	P-value
ROA	49.57	0.000	28.06	0.000
ROE	34.89	0.000	26.11	0.000
EPS	54.10	0.000	16.91	0.000
NPL	20.88	0.000	44.25	0.000
NCO	42.60	0.000	24.68	0.000
LoanR	64.47	0.000	46.86	0.000
VaR	53.08	0.000	25.58	0.000
LCR	91.50	0.000	29.56	0.000
CR	63.67	0.000	54.11	0.000
T1	49.99	0.000	49.73	0.000
D/A	35.02	0.000	27.02	0.000
D/E	46.38	0.000	26.24	0.000
BVC	32.33	0.000	30.13	0.000
ORP	50.38	0.000	40.49	0.000
Ln(Asset)	44.83	0.000	24.89	0.000
C/I	43.68	0.000	28.52	0.000

Table 4.17 Fisher's type unit root tests (UK)

4.3.4 Correlation matrix and variance inflation factors

Tables 4.18 and 4.19 show the correlations of the explanatory variables for the UK banks based on bank types. Similar to Chinese banks, no two variables had a correlation coefficient of over 0.8. Thus, no multicollinearity problem existed. However, we could also see that there is some relatively high correlations (close to and over 0.7) that exist between independent variables in matrices showed above. Thus, we apply VIF for our dataset to double-check for multicollinearity problems. Table 4.20 presents the VIFs for all variables based on types of banks. Similar to China, some variables show a relatively larger VIF than others, such as NPL for traditional and NCO for fintechs. Moreover, as they are credit-related variables, it shows higher interactions between credit-related variables and other risk management variables, which suggests the importance of credit risk management for both types of banks. As all VIFs are below 10, the results double-check the correlation matrix results and indicate that there are no issues of multiple correlation in this study.

	NPL	NCO	LoanR	VaR	LCR	CR	T1	D/A	D/E	BVC	ORP	Ln A	C/I
NPL	1												
NCO	0.6142	1											
LoanR	0.7516	0.5692	1										
VaR	0.1769	0.3917	0.1930	1									
LCR	-0.4054	-0.1906	-0.4447	-0.1246	1								
CR	0.0519	0.1104	0.0674	0.2932	-0.0575	1							
T1	-0.3323	-0.2094	-0.4011	-0.2263	0.2941	-0.3103	1						
D/A	-0.0884	-0.2488	-0.1596	-0.1076	0.0709	-0.4503	0.3406	1					
D/E	-0.0505	-0.2160	-0.1220	-0.1201	0.0823	-0.6083	0.3662	0.7460	1				
BVC	-0.3280	-0.2670	-0.3546	-0.1912	0.3543	-0.2317	0.2437	0.2603	0.2668	1			
ORP	0.0495	0.1921	0.0512	0.2050	0.0631	0.1112	-0.0269	-0.1732	-0.1490	-0.1653	1		
Ln A	0.4619	0.2557	0.5599	0.4257	-0.2953	0.4030	-0.2858	-0.6018	-0.5806	-0.3607	0.1709	1	
C/I	0.3893	0.1654	0.3521	0.2432	-0.3133	0.0940	-0.3339	0.2238	0.2024	-0.2087	0.0344	-0.0212	1

Table 4.18 Cross Correlation Matrix (UK traditional banks)

	NPL	NCO	LoanR	VaR	QR	LCR	CR	T1	D/A	D/E	BVC	ORP	Ln A	C/I
NPL	1													
NCO	0.4038	1												
LoanR	0.6593	0.5349	1											
VaR	-0.0344	0.0584	-0.0249	1										
QR	0.03129	0.1671	0.3014	0.3028	1									
LCR	-0.0952	-0.0789	-0.0447	-0.0724	-0.0803	1								
CR	0.5700	0.5117	0.5773	0.0386	0.5298	-0.1343	1							
T1	0.4379	0.4313	0.4436	-0.1531	0.1894	-0.0060	0.4599	1						
D/A	0.5497	0.4166	0.5362	-0.0522	0.35251	-0.1364	0.7826	0.5636	1					
D/E	-0.1525	-0.2056	-0.1562	-0.1932	-0.1617	0.1458	-0.0749	0.1485	0.0363	1				
BVC	0.2000	0.2387	0.2489	0.2163	0.2762	0.0861	0.0498	0.2736	0.0285	-0.2079	1			
ORP	0.7346	0.0188	0.0531	0.2352	0.7887	0.1208	0.1122	0.0156	0.2437	-0.086	0.3653	1		
Ln A	-0.6679	-0.5767	-0.6794	-0.0302	-0.5196	0.0072	-0.7201	-0.6102	-0.7685	0.0909	-0.1776	-0.2491	1	
C/I	-0.0185	0.1707	0.0129	--0.094	0.1673	0.1141	0.3367	0.3406	0.3647	-0.110	0.1644	0.2976	-0.3702	1

Table 4.19 Cross Correlation Matrix (UK challenger banks/fintechs)

Variable	Traditional banks	Challenger banks/fintechs
NPL	4.640	4.209
NCO	3.114	4.671
LoanR	4.330	3.396
VaR	2.433	2.204
LCR	1.456	1.189
CR	2.914	3.943
T1	1.800	2.656
D/A	4.021	4.895
D/E	4.468	1.454
BVC	1.354	2.182
ORP	1.136	2.190
Ln(Asset)	2.685	4.339
C/I	1.894	2.508

Table 4.20 Variance inflation factors (UK)

4.3.5 Tests for heteroscedasticity, endogeneity and model determination

Similar to China, we tested heteroscedasticity for the UK, White's general heteroscedasticity test is employed and the results are shown in Table 4.21. The results of White's test show that heteroscedasticity is present. Since heteroscedasticity causes standard errors to be biased, after finding the proper static panel model, we used robust standard errors.

	Bank type	ROA model	ROE model	EPS model
		p-values		
White's test	Traditional banks	0.0000	0.0000	0.0000
	Fintechs	0.0001	0.0000	0.0000

Table 4.21 Tests for heteroscedasticity

Moreover, we tested the endogeneity of the UK dataset through the DWH test. Table 4.22 show that we could not reject the null hypothesis (H_0: there is no endogeneity exist, and random-effects is more appropriate), we could see that there is no endogeneity problem for this study. Moreover, as mentioned in Section 4.2.5, we need to apply three tests to find the most appropriate approach to obtain our panel regression results. Table 4.22 shows the p-values of this test for the UK dataset. The results show that we need to reject the null hypothesis of the F test and Lagrange Multiplier test (H_0: the pooled

OLS is more appropriate). This suggests that models with fixed- and random-effects are more appropriate than pooled OLS with zero p-values for all dependent variables and bank types. All p-values are greater than 5% for all three dependent variables in the DWH test, so we cannot reject the null hypothesis. This suggests that random-effects models are suitable.

Test	Bank type	ROA model	ROE model	EPS model
			p-values	
F	Traditional banks	0.0000	0.0000	0.0000
	Fintechs	0.0000	0.0000	0.0000
LM	Traditional banks	0.0000	0.0000	0.0000
	Fintechs	0.0000	0.0000	0.0000
DWH	Traditional banks	0.0950	0.2248	0.1367
	Fintechs	0.2021	0.1990	0.0700

Table 4.22 Tests for determination the most appropriate approach for data analysis (UK)

4.3.6 Panel data regression analysis

Based on the three dependent variables, we constructed six random-effects panel data regression models to test the influences of risk variables on the bank performance variables based on different bank types. The random-effects model estimation results are shown in Tables 4.23 to 4.25.

	Traditional banks		Fintechs	
	Estimations	Robust Std. Err	Estimations	Robust Std. Err
Intercept	-0.1387	0.0985	0.1899	0.1092
Non-performing loan ratio	-0.0306*	0.1173	-4.3907***	1.1149
Net Charge-off rate	-0.0473	0.0864	-7.4907***	3.0570
Total loan loss ratio	-0.1579***	0.1114	-0.6979	0.1262
Value at risk	-0.0001*	0.00005	0.0236***	0.0130
Liquidity coverage ratio	0.0006	0.0035	0.0330**	0.0718
Current ratio	0.1889***	0.0942	0.0943**	0.1006
Tier 1 capital ratio	0.0357**	0.0129	0.1497	0.0761
Debt-to Asset ratio	-0.0175***	0.0119	-2.0421***	1.1462
Debt-to-Equity ratio	-0.0007	0.0006	-0.0038**	0.0061
Brand value change %	-0.0108*	0.0130	0.1043	0.1050
Operational risk %	-0.0008*	0.0030	-0.5897***	0.2346
Ln(Asset)	0.0032**	0.0013	0.0380	0.0237
Cost-to-Income ratio	-0.0082**	0.0051	-0.0006	0.0115
R^2_{within}	0.5587		0.6088	
$R^2_{between}$	0.5674		0.6522	
$R^2_{overall}$	0.3211		0.4697	
No. of Obs.	97		52	

Table 4.23 Random-effects estimation results (ROA, UK)

Note: *, **, ***represent significance at the 10%, 5% and 1% levels respectively.

With regards to ROA, the results are consistent for the credit risk variables with Chinese banks. All variables have negative influences on the UK traditional banks and fintechs. In more detail, NPL and LoanR have a significant negative impact on ROA for traditional banks, while NPL and NCO show significant negative influences on fintechs. For traditional banks, the LoanR has the largest coefficient number, a 1% increase of the LoanR will lead to a 0.1579% decrease of the ROA where NPL and NCO could lead to 0.0306% and 0.0473% representatively. When managing credit risks, managers should consider more on the LoanR with its higher significance level and coefficient value. Moreover, as shown in Figure 4.9, the credit risk level is more under control with increased efficiency. It indicates that UK traditional banks performed well in credit risk management. For fintechs, consistent results were also seen. NPL and NCO show significant negative impacts on ROA as they showed in China. With regards to coefficient values, the NCO has the largest coefficient number, a 1% increase of the

NCO will lead to a 7.4907% decrease of the ROA where NPL and LoanR could lead to 4.3907% and 0.6979% decrease, representatively. Thus, with a higher significance level and coefficient values, managers in fintechs should focus more on NCO in credit risk management. In addition, in both China and the UK, fintechs provide higher coefficient values than in traditional banks which suggests that credit risk has a higher impact on fintechs, and that managers should pay more attention to reducing credit risks.

VaR shows a significant influence on ROA for both UK traditional banks and UK fintechs, where it is only significant for Chinese fintechs. This suggests that the market movement has a higher impact on UK banks than Chinese banks. It shows a negative impact on traditional banks which means that high market risk leads to poor ROA performance. 1% increase in VaR will lead to a 0.0001% decrease in traditional banks' ROA. However, it shows a positive impact on fintechs which suggests that higher market risks lead to a better ROA performance. 1% increase in VaR will lead to a 0.0236% increase in fintechs ROA. This result proves the complexity of the market risks, which suggests that the UK banks should take extra care about market risks.

With regards to our estimates of liquidity and capital risk variables, similar to China, all three variables are positively impact on ROA for both types of banks, which suggests that increasing the liquidity and capital holding level would help UK banks increase ROA performance. In more detail, CR and T1 have a significant positive impact ROA for traditional banks at 1% and 5% significance level, respectively. In comparison, both LCR and CR show significant positive influences on fintechs at the 5% significance level. For coefficient values, a 1% increase in LCR will lead to a 0.0006% increase in ROA, where CR and T1 could lead to 4.3907% and 0.6979%, representatively, for the UK traditional banks. For fintechs, LCR will lead to a 0.0330% increase in ROA, where CR and T1 could lead to 0.0943% and 0.1497%, representatively. For both types of UK banks, as CR has the highest significance level combined with a relatively high coefficient value, managers should take extra care about CR. With regards to debt level, D/A shows a significant negative impact on ROA for both types of banks at the 1% significance level in the UK. A 1% increase in D/A will lead to a 0.0175% decrease in

ROA for traditional banks, In contrast, a 2.0421% decrease in ROA for fintechs. Moreover, D/E has a significant negative relationship with ROA for the UK fintechs, whereas it shows a positive impact on Chinese fintechs. This suggests that the higher debt level will reduce ROA performance for UK fintechs. Considering the significance level and coefficient value, both types of UK banks should consider more on the D/A than D/E.

In addition, there is evidence of a positive relationship between bank size and ROA in the UK traditional banks and fintechs, which suggests that larger banks tend to have higher returns on assets. Moreover, as ln(asset) only significantly positively influences the traditional banks' ROA, where a 1% increase in ln(asset) will lead to a 0.0032% increase in ROA. This suggests the higher importance of size in traditional banks performance. Together with Chinese traditional banks' results for ln(asset), this shows that bank size increases performance to a certain level and then decreases performance after that point, this result is consistent with previous studies(e.g. Athanasoglou et al., 2008; Berger & Humphrey, 1994). For reputational risks, the BVC shows a positive impact on both types of banks. For UK traditional banks, it shows a significantly positive impact on ROA at the 10% significance level, a 1% increase in BVC will lead to a 0.0108% increase in their ROA. This suggests that increase banks' reputation could help them increase their ROA performance. Thus, UK traditional banks should aim to have aa increasing reputation during operations. For the UK fintechs, a 1% increase in BVC will lead to a 0.1043% increase in UK fintechs' ROA. Although it is not significant, increasing reputation during operations is still good for the UK fintechs.

Finally, with regards to operational risk variables, ORP has a significant negative influence on the ROA of both types of banks (10% significance level for traditional banks and 1% significance level for the fintechs). A 1% increase in ORP will lead to a 0.0008% decrease in ROA for traditional banks and a 0.5897% decrease for fintechs. This proves that when operational risks occur, bank performance decreases because of higher costs occurred. C/I confirms similar results, but it was only significant in traditional bank estimation at the 5% significance level. With regards to coefficient value, a 1% increase in C/I will lead 0.0082% decrease in ROA for UK traditional banks and a 0.0006% decrease for the UK fintechs. This result shows that the UK traditional banks should consider operational risks carefully as both variables are significant. For fintechs, managers should pay more attention to ORP with its higher significance and coefficient value.

Similar to China, besides interpreting variables, we looked at the R^2 for our ROA models. R^2(within) shows a 56% variation within one traditional banks over time and a 61% variation within one fintech over time. R^2(between) shows 57% variation between traditional banks and 65% variation between fintechs. R^2(overall) shows 32% for traditional banks and 47% for fintechs. We could find out that fintechs have higher R^2s, which indicate higher variation was presented in fintechs.

	Traditional banks		Fintechs	
	Estimations	Robust Std. Err	Estimations	Robust Std. Err
Intercept	0.3443	0.5182	-0.2011	0.5044
Non-performing loan ratio	-0.7435***	0.6133	-3.1545***	0.5346
Net Charge-off rate	-1.1569***	0.4547	-5.4655**	0.2673
Total loan loss ratio	-0.0001	0.5589	-0.5009	0.0610
Value at risk	0.0003*	0.0003	0.0378**	0.5916
Liquidity coverage ratio	0.0115*	0.0188	0.0230	0.0336
Current ratio	0.3661	0.4935	0.1122*	0.4658
Tier 1 capital ratio	0.1022***	0.1027	0.1339	0.3624
Debt-to Asset ratio	-0.712***	0.0623	-1.883***	0.6763
Debt-to-Equity ratio	-0.0008*	0.0008	-0.0037*	0.2920
Brand value change %	0.0080*	0.0719	0.0903	0.0732
Operational risk %	-0.0096**	0.0157	-0.5681***	0.1066
Ln(Asset)	-0.0038	0.0066	0.0247	0.0108
Cost-to-Income ratio	-0.2220***	0.0271	-0.0006*	0.0526
R^2_{within}	0.6322		0.5034	
$R^2_{between}$	0.6802		0.5546	
$R^2_{overall}$	0.4701		0.3983	
No. of Obs.	97		52	

Table 4.24 Random-effects estimation results (ROE, UK)

Note: *, **, ***represent significance at the 10%, 5% and 1% levels respectively

Besides ROA, ROE also shows consistent results through the random-effects panel data regression estimates in Table 4.22. Firstly, all credit risk variables negatively impact ROE, while fintechs have a higher impact with larger estimates than the UK traditional banks. For both types, NPL and NCO have a significant negative impact on ROE. In more detail, NPL and NCO show their significance at the 1% significance level for UK traditional banks. In contrast, for UK fintechs, NPL and NCO show their significance at the 1% and 5% significance level, respectively. With regards to coefficient values, for traditional banks, the NCO has the largest coefficient number, a 1% increase of the NCO will lead to a 1.1569% decrease of the ROE where NPL and LoanR could lead to 0.7435% and 0.0001% representatively. For fintechs, the NCO also has the largest coefficient number, a 1% increase of the NCO will lead to a 5.4655% decrease of the ROE where NPL and LoanR could lead to 3.1545% and 0.5009% decrease, representatively. This result indicates that reducing credit risks would help the UK banks to achieve a better ROE. Managers should consider more on the NCO with its stronger significance level and coefficient values. Fintechs should consider more on credit risk management with higher coefficient values for credit risk variables.

Then, with regards to the market risk variable, VaR shows a significant positive impact on ROE for both types of banks. This suggests that if the UK banks catch the opportunities of the market movement, they can achieve a better ROE when facing market risks. A 1% increase in VaR will lead to a 0.0003% increase in traditional banks' ROE and a 0.0378% increase in fintech' ROE. Thus, our findings supported previous who found market risk may cause loss to banks (e.g., Frey and McNeil, 2002; and Kerkhof et al., 2010) as well as bring opportunities for banks (e.g. Willam, 2016).

Thirdly, with regard to the liquidity and capital risk variables, for the UK traditional banks, LCR and T1 show a significant positive influence on ROE at the 10% and 1% significant level, respectively. For coefficient values, a 1% increase in LCR will lead to a 0.0115% increase in ROE, where CR and T1 could lead to 0.3661% and 0.1022%, representatively. T1 shows its importance in liquidity and capital risk management with a higher significant level and a relatively coefficient value. Thus, the UK traditional banks need to meet T1 legal requirements during operation. D/A and D/E show a significant negative impact on ROE at the 1% and 10% significant level. A 1% increase in the D/A or D/E will lead to a 0.712% or 0.0008% decrease in ROE. With the higher significance level and coefficient values, managers should focus more on D/A during risk management. Thus, in order to have a higher ROE, the UK traditional banks should increase their liquidity and capital holding level and reduce their debt level. For fintechs, CR shows a significant positive impact at the 10% significant level, and D/A and D/E show a significant negative impact on ROE with the 1% and 10% significant level, respectively. With regards to coefficient values, a 1% increase in LCR, CR or T1 will lead to a 0.023% or 0.1122% or 0.1339% increase in ROE, while a 1% increase in D/A or D/E will lead to a 1.883% or 0.0037% decrease in ROE. Thus, in order to have a higher ROE, UK fintechs should increase the liquidity and current asset holding levels and reduce debt levels. Managers should focus more on CR based on its higher significance level for liquidity risk management and D/A based on its higher significance level and coefficient value for debt level management.

Next, concerning the reputational risk variable, BVC has a significantly positive impact on ROE at the 10% significance level for traditional banks. A 1% increase in BVC will lead to a 0.008% increase in the bank's ROE, which shows the importance of keeping developing the bank brand value. However, BVC is not significant for fintechs. This does not show that BVC is not important in fintechs' operations but instead suggests that the BVC is not a highly significant influence on the fintechs' ROE during the developing stage of such fintechs. Managers still need to keep fintechs’ BVC healthy and increased, as a 1% increase in BVC will lead to a 0.0903% increase in fintechs' ROE. Similar to China, ln(asset) also shows a positive influence on ROE for fintechs but a slightly negative influence for traditional banks. A 1% increase in ln(asset) will lead to a 0.0038% decrease in traditional banks' ROE, but 0.0247% increase for fintechs. Although the ln(asset) are not significant for both types of banks, managers still need to keep their asset at a healthy level, which could help them to have a good performance.

Finally, with regards to operational risk variables, both ORP and C/I have significant negative impacts on ROE for both types of banks. In more detail, ORP shows its significant at the 5% level for traditional banks and 1% level for fintechs, where C/I shows it significant at the 1% level for traditional banks and 10% level for fintechs. This confirms that keeping bank operations smooth and decreasing the cost of operations could help the UK banks improve their ROE. With regards to coefficient values, a 1% increase in ORP will lead to a 0.0096% decrease in ROE for traditional banks and a 0.5681% decrease for fintechs. A 1% increase in C/I will lead 0.2220% decrease in ROE for UK traditional banks and a 0.0006% decrease for the UK fintechs. This result shows that both types of the UK banks should consider operational risks carefully as both variables are significant. In addition, as ORP has a higher coefficient value than C/I, managers in fintechs should pay more attention to their ORP.

Besides interpreting variables, we looked at the R^2 for our ROE model. R^2(within) shows a 63% variation within one traditional banks over time and a 50% variation within one fintech over time. R^2(between) shows 58% variation between traditional banks and 55% variation between fintechs. R^2(overall) shows 47% for traditional banks and 39% for fintechs. We could find out that traditional banks have higher R^2s, which indicate higher variation was presented in traditional banks.

	Traditional banks		Fintechs	
	Estimations	Robust Std. Err	Estimations	Robust Std. Err
Intercept	-4.2179	6.8939	-0.1300	0.4348
Non-performing loan ratio	-6.4574**	4.7601	-10.5275**	4.6189
Net Charge-off rate	-0.8104	5.5770	-4.4348	2.3172
Total loan loss ratio	-0.0077*	0.6055	-5.3857*	5.0986
Value at risk	-0.0016*	0.0032	-0.0172*	0.0052
Liquidity coverage ratio	0.0712	0.1617	0.0581	0.2897
Current ratio	0.8481**	0.4436	1.6099***	1.4791
Tier 1 capital ratio	0.7480***	1.4931	1.3621	1.3152
Debt-to Asset ratio	-1.2392	1.3362	-0.4545	0.5893
Debt-to-Equity ratio	-0.0369**	0.0479	-0.0115*	0.0248
Brand value change %	0.3566	0.4639	0.4964***	0.6197
Operational risk %	-0.0238	0.1363	-2.9088***	0.9388
Ln(Asset)	0.4533*	0.3226	0.2489***	0.0960
Cost-to-Income ratio	-0.2203**	0.2704	-0.8203***	0.4639
R^2_{within}	0.3092		0.5457	
$R^2_{between}$	0.4168		0.6034	
$R^2_{overall}$	0.2339		0.4522	
No. of Obs.	70		30	

Table 4.25 Random-effects estimation results (EPS, UK)

Note: *, **, ***represent significance at the 10%, 5% and 1% levels respectively.

Finally, we observe how different types of risk variables influence the EPS of the listed banks. Some consistent results are obtained. Firstly, all credit risk variables negatively impact EPS. However, NCO was not significant for either type of bank, which indicates that the NCO affects EPS negatively but is not a critical variable. For both types, NPL and NCO have a significant negative impact on ROE. In more detail, NPL and LoanR show their significance at the 5% and 10% significance level for both types of UK banks. With regards to coefficient values, for traditional banks, the NPL has the largest coefficient number, a 1% increase of the NPL will lead to a 6.4574% decrease of the EPS where NCO and LoanR could lead to 0.8104% and 0.0077% representatively. For fintechs, the NPL also has the largest coefficient number, a 1% increase of the NNPL will lead to a 10.5275% decrease of the EPS where NCO and LoanR could lead to 4.4348% and 5.3857% decrease, representatively. This result indicates that reducing credit risks would help the UK banks to achieve a better EPS. Managers should consider more on the NPL with its stronger significance level and coefficient values. Fintechs should consider more on credit risk management with higher coefficient values for credit risk variables.

Secondly, VaR has a significant negative influence on both types of UK banks at the 10% significance level. This indicates that the market movement influences EPS, as EPS is gained from the bank market performance. A 1% increase in VaR will lead to a 0.0016% increase in traditional banks' EPS and a 0.0172% increase in fintech' EPS. In addition, VaR shows a different impact on different performance variables. This indicates the complexity of market risks and that managers should pay attention and stay alert to market movement and search for the balance point to reach better performance.

With regards to liquidity and capital risk variables, results are consistent. For the UK's traditional banks, CR and T1 show significant positive impacts and D/E shows a significant negative influence on EPS at the 5% significance level, 1% and 5%significance level, representatively. For coefficient values, a 1% increase in LCR will lead to a 0.0712% increase in EPS, where CR and T1 could lead to 0.8481% and 0.748%, representatively. A 1% increase in the D/A or D/E will lead to a 1.2392% or 0.0369% decrease in EPS. With the higher significance level and coefficient values, managers should focus more on CR during liquidity risk management and D/E during debt level management. This indicates that if the UK traditional banks have higher current assets and tier one capital holding levels and a lower debt level, better performance of EPS could be shown. For the UK fintechs, only CR and D/E show significant influence on EPS at 1% and 10% significance level, representatively. For coefficient values, a 1% increase in LCR will lead to a 0.0581% increase in EPS, where CR and T1 could lead to 1.6099% and 1.3621%, representatively. A 1% increase in the D/A or D/E will lead to a 0.4545% or 0.0115% decrease in EPS. With the higher significance level and coefficient values, managers in fintechs also should focus more on CR during liquidity risk management and D/E during debt level management. This suggests that if the UK fintechs have a higher current asset level and lower debt level, then a higher EPS will be shown for them.

With regards to BVC, it has a positive impact on banks' EPS. However, BVC has no significant influence on EPS for the UK traditional banks. One possible reason for this is the limited development of traditional banks in the UK during the investigating time period. However, managers still need to keep their brand values healthy and ideally increase their brand values, as a 1% increase in BVC will lead to a 0.3566% increase in traditional banks' BVC. For fintechs, as they keep increasing their brand value during these years, the BVC is significantly positively related to fintechs' EPS at the 1% significance level. Concerning the coefficient value, a 1% increase in BVC will lead to a 0.4964% increase in fintechs' EPS Managers need to consider fintechs' BVC more careful than traditional banks with its higher significance level and coefficient value. Similar to Cheung et al. (2011), our results proved that increasing banks' brand values could help them increase their EPS performance.

Moreover, ln(asset) has a significant positive relationship to EPS in both types of banks with the 10% significance level for traditional banks and the 1% significance level for fintechs. A 1% increase in ln(asset) will lead to a 0.4533% increase in traditional banks' EPS and 0.2489% increase for fintechs. This suggests that with more asset, the UK banks will have a better EPS. Finally, operational risk variables provide consistent results. ORP and C/I have negative impacts on EPS for both types of banks. In more detail, ORP shows its significant at the 1% level for fintechs, where C/I shows it significant at the 5% level for traditional banks and 1% level for fintechs. This confirms that keeping bank operations smooth and decreasing the cost of operations could help the UK banks improve their EPS. With regards to coefficient values, a 1% increase in ORP will lead to a 0.0238% decrease in EPS for traditional banks and a 2.9088% decrease for fintechs. A 1% increase in C/I will lead 0.2203% decrease in EPS for UK traditional banks and a 0.8203% decrease for the UK fintechs. Thus, with a relatively weak situation of operational efficiency showed in Figure 4.13, the UK traditional banks should cut unnecessary costs to receive a better EPS. The UK fintechs should build their operational risk management system to control costs for better EPS performance.

Similarly, besides interpreting variables, we looked at the R^2 for our EPS models. R^2(within) shows a 31% variation within one traditional banks over time and a 55% variation within one fintech over time. R^2(between) shows 42% variation between traditional banks and 60% variation between fintechs. R^2(overall) shows 23% for traditional banks and 45% for fintechs. We could find out that fintechs have higher R^2s, which indicate higher variation was presented in fintechs.

In general, the estimates from panel data regression models provided consistent results for the UK traditional banks and fintechs. Differences also existed between the UK traditional banks and fintechs. Similar to the results from China, the first difference is showed in credit risk. Although all credit risk variables show negative impacts on all three dependent variables, the impact level is different. It shows a higher level of impact on fintechs than traditional banks. This result shows the importance of credit risk management for fintechs. With the comparisons showed in Section 4.3.1, we see that the UK traditional banks improved their credit risk management efficiency during the investigated time period. Thus, fintechs should learn from traditional banks' experience to more efficiently manage credits risk in the future. The second difference is market risk. Based on the dependent variables, VaR shows a different impact direction for both traditional banks and fintechs. This is due to the complexity of market movements. Thus, both types of banks should monitor market changes and find a balanced point of VaR to receive better performance.

Thirdly, BVC has a negative impact on the UK traditional banks' ROA, while it positively influenced the UK fintechs performance. The possible reason for this could be that UK traditional banks did not develop their brand value much during the investigated time period, while fintechs increased their brand value continuously. The final difference is ln(asset). It has a positive influence on fintechs, but it has a slightly negative impact on ROE for the UK traditional banks, whereas it has a significant positive impact on ROA and EPS for the UK traditional banks. The reason for the negative impact exits should be similar to Chinese traditional banks. Traditional banks have been established for a long time and have reached a relatively high assets level. Maintaining a safe level or reducing useless assets could help them perform better. Our results confirmed some previous studies (e.g., Athanasoglou et al., 2008; Berger & Humphrey, 1994), as asset increasing to a certain level, it will hurt bank performance. However, as the UK banks are not as large as Chinese traditional banks, ln(asset) does not have a significant impact on ROE. Thus, the UK traditional banks should maintain and increase their asset levels to receive better performance.

Similar to the Chinese results, besides differences, the results also showed consistent results between types of bank. Firstly, reducing credit risks could help both types of banks increase their performance, given their negative impacts. Secondly, both types of banks should follow the legal requirements to increase their liquidity and capital holding level and decrease their debt level. Based on their different significance level, managers should have different focuses depending on their bank type. Thirdly, because of the negative influence of operational risk variables, controlling operational issues and costs could increase performance for both types of banks. Finally, developing the bank's reputation could help both types of banks increase their performance. Therefore, for both traditional banks and fintechs, a better reputation, healthy liquidity conditions, efficient credit risk management, lower debt and cost levels and alertness to market movements could provide better performance in both returns and share market.

4.3.7 GMM estimates for the UK

Following section 4.2.7, this section will provide GMM to check if our results from the random-effects model are robust for UK banks. Similar to China, even though we called GMM a robustness checks for random-effects models, the results from GMM are as important as we got from random-effects. We will use and compare both approaches' results (Random-effects and GMM) to build our discussion and conclusions. Tables 4.26 to 4.28 GMM estimates for the impacts of risks on the bank performance (ROA, ROE and EPS, respectively) in the UK.

	Estimations	
	Traditional banks	Fintechs
Intercept	-0.0433	-0.0276
One period lag of ROA	0.1427*	0.1348***
Non-performing loan ratio	-0.0551**	-0.0323
Net Charge-off rate	-0.1368	-0.5443***
Total loan loss ratio	-0.1293*	-0.2817***
Value at risk	-0.0001**	0.0002*
Liquidity coverage ratio	0.0005*	0.0045***
Current ratio	0.0056*	0.0150
Tier 1 capital ratio	0.0040**	0.0228**
Debt-to Asset ratio	-0.0216*	-0.0196
Debt-to-Equity ratio	-0.0017	-0.0001**
Brand value change %	0.0244***	0.0034
Operational risk %	-0.0021	-0.0021***
Ln(Asset)	0.0128*	0.0028*
Cost-to-Income ratio	-0.0220***	-0.0150***
F-test	502.3***	108.1***
Sargan Test (p-value > χ^2)	43.3 (0.293)	31.4(0.300)
AR(1)	z =-3.56 p-value = 0.00	z = -2.9 p-value = 0.00
AR(2)	z = -0.32 p-value = 0.74	z = -0.4 p-value =0.68
No. of Obs.	97	52

Table 4.26 GMM estimation results (ROA, UK)

Notes: *, **, ***represent significant at 10%, 5% and 1% respectively.

Sargan test is the test for over-identifying restrictions in GMM dynamic model estimation.

AR(1) and AR(2) are Arellano-Bond test that average autocovariance in residuals of order 1 and 2 is 0 (H_0: no autocorrelation).

Firstly, ROA was selected as the dependent variable to establish two GMM estimates based on bank type. Similar to China, the F-statistics show the significance of the variables. The Sargan test shows that there is no evidence of over-identifying restrictions, and the Arellano-Bond test shows the consistency of our estimates for the independent variables.

For the UK's traditional banks, firstly, the significant coefficient of the lagged ROA confirms the dynamic character of the model specification. δ takes a value of 0.14 which suggests that the performance of the UK's traditional banks seems to persist. This implies that the UK's traditional banks have a relatively competitive structure. This shows the higher competitiveness of the UK traditional banks than the Chinese traditional banks.

Turning to the other independent variables, similar results are presented as shown in our random-effects panel data regression models. Firstly, the credit risk variables have negative impacts. This suggests that higher credit risks lead to poor performance. In details, NPL and LoanR also significantly negatively impact the ROA at 5% and 10% significance level. With regards to coefficient values, a 1% increase of the NPL will lead to 0.0551% of the ROA, where NCO and LoanR could lead to 0.1368% and 0.1293% representatively. Similar to random-effects models, LoanR shows its importance in credit risk management in both significance level and coefficient value. Thus, this suggests that managers should pay more attention to LoanR during credit risk management. Moreover, the values of the estimates are larger than were showed for Chinese traditional banks. This suggests that the UK traditional banks should be more concerned with these credit risk variables.

With regards to market risk, VaR has a significant negative impact on ROA. This suggests that higher market risk could decrease the ROA performance of the UK traditional banks. The result is also similar to the results from random-effects estimates, which suggest that UK traditional banks should reduce or keep alert to the market risks.

Next, with regards to the liquidity, capital and debt level variables, consistent results are shown compared with our random-effects panel data regression models. The positive relationship between liquidity and capital holding level and bank performance and the debt level variables is negatively related to bank performance. LCR, CR and T1 all show significant positive impacts on ROA with 10%, 10% and 5%, respectively. With regards to coefficient values, a 1% increase in LCR will lead to a 0.0005% increase in ROA, where CR will lead to a 0.0056% increase and T1 will lead to a 0.004% increase. The results indicate that increasing the liquidity and capital holding level could increase their performance. For debt level variables, D/A is significant for ROA at the 10% level. With regards to coefficient values, a 1% increase in D/A will lead to a 0.0216% decrease in ROA, where D/E will lead to a 0.0017% decrease in ROA. Similar to the results from random-effects, the GMM results suggest that a lower debt level could help banks to receive better performance. Managers should consider more on D/A with its higher significance level and coefficient value.

With regards to the operational risk variables, similar to our panel data regression models, both variables negatively affect ROA. C/I shows a higher significant negative impact on the UK traditional banks at the 1% significance level. Based on the coefficient values, a 1% increase of ORP or C/I will lead to 0.0021% or 0.022% of changes in ROA. The higher significant level and coefficient value for the C/I than in China, which suggests that together with concerning themselves with their particular operational risks, UK traditional banks also need to increase their operational efficiency. In addition, a similar result is shown in the reputational risk variable. BVC shows a significant positive impact on ROA at a 1% significance level, where a 1% increase in BVC will lead to a 0.0244% increase in their ROA. This means that increasing reputation could help banks to increase ROA performance. Compared to China, as reputational risk variable shows a higher coefficient value and significance level, UK traditional banks need to be concerned more with their brand value when managing bank risks than Chinese traditional banks.

Finally, with regards to bank size, it is significant and positive impacts on ROA at the 10% significance level. A 1% increase in ln(asset) will lead to a 0.0128% increase in ROA. This result is consistent with the results obtained from our random-effects models.

For UK fintechs, The F-statistics show the significance of the variables. The Sargan test shows there is no evidence of over-identifying restrictions. The AR tests show that the estimates of independent variables are consistent. With regard to lagged dependent variables, although it is not significant, the coefficient of the lagged ROA shows the dynamic character of the model specification. δ takes a value of approximately 0.13, which suggests that the performance of the UK fintechs seems to persist to a competitive market structure in ROA. However, it is lower than value showed in Chinese fintechs. This shows the higher competitiveness of Chinese fintechs than the

UK fintechs.

Estimates for the independent variables show results for ROA consistent with our random-effects panel data regression models. Firstly, all credit risk variables have negative impacts and the coefficient values of these variables are larger than were obtained for traditional banks. Moreover, NCO and LoanR are significantly negatively impacting the ROA at the 1% significance level. In more detail, a 1% increase in NPL will lead to a 0.0323% decrease in ROA, NCO shows 0.5443% and LoanR shows 0.2817%. This confirms that credit risk hurts bank performance as in traditional banks, but that fintechs should be more concerned with these credit risk variables, as these variables have higher coefficient values and significance levels. With regards to market risks, VaR shows a positive relationship with bank performance and is significant at the 10% level for ROA. A 1% increase in VaR will lead to a 0.0002% increase in UK fintechs' ROA.

With regards to the capital and liquidity risk variables, similar results are presented compared with results from random-effects models. Fintechs with a higher level of capital and liquidity holdings level and meet legal requirements for these variables could obtain better performance. In more detail, all three capital and liquidity variables positively impact the ROA. Only LCR and T1 have a 1% and 5% significantly impact, respectively. Based on coefficient values, a 1% increase in LCR will lead to a 0.0228% positive change of ROA, where CR shows 0.015% and T1 shows 0.0432% positive changes to ROA. With regards to debt variables, the results show that both D/A and D/E have negative impact on UK fintechs' ROA. In more detail, D/E shows its significance at the 5% level to the ROA. A 1% increase in D/A or D/E will lead to a 0.0196% or 0.0001% decrease in ROA. This result is consistent with our random-effects panel data regression models. Moreover, the results also present similar results on ROA compared with traditional banks' results. This suggests that a lower debt level could help UK fintechs to achieve better performance. Thus, prioritising these variables in risk management based on their estimated values and significance could help managers achieve better efficiency and performance.

With regards to operational risk variables, both variables also show significant negative impact on ROA at the 1% significance level. A 1% change in ORP will lead to a 0.0021% decrease and C/I will lead to a 0.015% decrease in fintechs' ROA. Similar to GMM estimates shown in traditional banks, together with control over particular operational risks, UK fintechs also need to control their overall costs and increase their operational efficiency to obtain better performance. With regards to reputational risk variables, consistent results are shown compared with random-effects estimates for the UK fintechs and GMM estimates for the UK traditional banks. BVC also shows a positive impact on ROA, where a 1% increase in BVC will lead to a 0.0034% increase in ROA. Although it does not significantly impact the ROA, the manager still needs to keep fintech's brand value healthy, as increased reputation could help fintechs achieve better performance. Finally, similar to the random-effects estimates for ROA, there is evidence of a positive relationship between size and ROA performance. At the 10% of significance level, a 1% increase of fintechs' ln(asset) will lead to a 0.0028% increase of fintechs' ROA, which suggests that increasing size tends to better performance.

	Estimations	
	Traditional banks	Fintechs
Intercept	0.2661	0.6323
One period lag of ROE	0.0246	0.0738*
Non-performing loan ratio	-0.9118**	-1.3867*
Net Charge-off rate	-2.6493	-5.8154*
Total loan loss ratio	-1.4290***	-4.5436***
Value at risk	-0.0005*	0.0026
Liquidity coverage ratio	0.0075	0.0033***
Current ratio	0.1672	0.3108*
Tier 1 capital ratio	0.2011**	0.5045
Debt-to Asset ratio	-0.1288**	-0.1855*
Debt-to-Equity ratio	-0.0202	-0.0003*
Brand value change %	0.2119*	0.0774
Operational risk %	-0.0067	-0.0285*
Ln(Asset)	-0.0562*	0.0706*
Cost-to-Income ratio	-0.3180***	-0.1966***
F-test	767.7***	1198.6***
Sargan Test (p-value > χ^2)	49.8(0.115)	34.4(0.188)
AR(1)	z = -2.74 p-value = 0.00	z = -2.53 p-value = 0.006
AR(2)	z = -0.54 p-value = 0.58	z = -0.12 p-value = 0.90
No. of Obs.	97	52

Table 4.27 GMM estimation results (ROE, UK)

Notes: *, **, ***represent significant at 10%, 5% and 1% respectively.

Sargan test is the test for over-identifying restrictions in GMM dynamic model estimation.

AR(1) and AR(2) are Arellano-Bond test that average autocovariance in residuals of order 1 and 2 is 0 (H_0: no autocorrelation).

Besides ROA, GMM estimates for ROE also show consistent results compared with random-effects panel data regression estimations in Table 4.27. For traditional banks, similar to GMM for traditional banks in ROA, the F-statistics show the significance of the variables. The Sargan test shows there is no evidence of over-identifying restrictions. The AR tests show that the estimates of independent variables are consistent. For the lagged dependent variable, the significant coefficient of the lagged ROE confirms the dynamic character of the model specification. δ takes a value of 0.0246 when performance is measured by ROE. Although it is not significant, the result still could suggests that the performance of the UK's traditional banks seems to persist. This implies that the UK's traditional banks have a relatively competitive structure. This shows the higher competitiveness of the UK traditional banks than the Chinese traditional banks.

Turning to the other independent variables, the results here for the dependent variables are consistent with our random-effect panel data regression models. Firstly, credit risk variables have negative impacts. This suggests that higher credit risks lead to poor ROE for UK traditional banks. In details, NPL and LoanR significantly negatively impact the ROE at the 5% and 1% level. In these credit risk variables, the NCO has the largest coefficient number. A 1% increase of the NCO will lead to 2.6493% decrease of the ROE where NPL and LoanR could lead to 0.9118% and 1.429%, representatively. Similar to random-effects models, LoanR shows its importance in credit risk management based on the highest significance level and relatively higher coefficient value. With regards to market risk variables, VaR has a significant negative impact on ROE at the 10% significance level. However, the results from random-effects estimates show that VaR has a significant positive influence on ROE. As we tested, there is no endogeneity problem exist in our dataset, and the two coefficient values for VaR in Random-effects and GMM are closed. The difference showed here suggests that the UK traditional banks should be concerned more with market risks. Moreover, as the results for the other two dependent variables are consistent, the UK traditional banks should keep VaR at a reasonable level and reduce the risk if possible, to achieve better performance.

Regarding the capital and liquidity risk variables, consistent results also show in GMM compared with random-effects. T1 has significant positive impacts on ROE with a 5% significance level, where a 1% increase in T1 will lead to a 0.2011% increase in ROE. For LCR and CR, a 1% increase in LCR or CR will lead to a 0.0075% or 0.1672% increase in traditional banks' ROE. Even though LCR and CR do not appear significant in the ROE model, with its positive influence, managers should still keep LCR and CR pass the legal requirement and at a healthy level. The results show the importance of T1 for traditional banks. Thus, managers should follow the regulation requirements (e.g.

Basel Accords) and increasing the capital holding level could help banks increase their performance. We further notice that the debt level variables are negatively related to bank performance, where D/A shows its significance for ROE at the 5% level. In more detail, a 1% decrease in D/A will lead to a 0.1288% increase in ROE where D/E shows a 0.0202% influence in ROE. Similar to the results from random-effects, the GMM results suggest that a lower debt level could help banks receive better performance. Managers should consider more on D/A with its higher significance level and coefficient value.

With regards to operational risk variables, GMM also provides results consistent with our random-effects panel data regression models. Both variables affect ROE negatively, where C/I is significant at the 1% level. Based on the coefficient values, a 1% increase of ORP or C/I will lead to 0.0067% or 0.318% decreases in ROE. Similar to the random-effects for ROE in traditional banks, as coefficient value for C/I changes ROE more, together with its higher significance level, managers in UK traditional banks should be concerned more with overall operational risks. For reputational risk variables, BVC shows a significant and positive impact on ROE at the 10% significance, where a 1% increase in BVC will lead to a 0.2119% increase in their ROE. This suggests that increasing reputation could help banks increase ROE performance. Finally, the coefficient for bank size is significant and negatively impacts bank performance at the 10% significance level for ROE. This result is consistent with Tan (2016), who also found a negative relationship between size and bank performance. Overall, similar to random-effects estimates, most of the coefficient values in ROE are around ten times larger than coefficient values in ROA. The possible reason could be that the ROE values are around ten times larger than ROA. The GMM further confirmed this result.

For UK fintechs, The F-statistics show the significance of the variables. The Sargan test shows there is no evidence of over-identifying restrictions. The AR tests show that the estimates of independent variables are consistent. With regard to lagged dependent variables, the coefficient of the lagged ROE shows the dynamic character of the model specification. δ takes a value of approximately 0.0738, which suggests that the performance of the UK fintechs seems to near to a perfectly competitive market structure in ROE.

Estimates for the independent variables show results for ROE consistent with our random-effects panel data regression models. Firstly, all credit risk variables have negative impacts and the coefficient values of these variables are larger than were obtained for traditional banks. Moreover, all three variables (NPL, NCO and LoanR) significantly negatively impact the ROE at 10%, 10% and 1% significance level. For coefficient values, a 1% increase in NPL will lead to a 1.3867% decrease in ROE, NCO shows 5.8154% and LoanR shows 4.5436%. We could see that the coefficient values are larger than they showed in traditional banks like random-effects models. This confirms that credit risk hurts bank performance as in traditional banks, but that fintechs should be more concerned with these credit risk variables. With regards to market risks, VaR shows a positive relationship with bank performance for ROE, where a 1% increase in VaR will lead to a 0.0026% increase in ROE.

With regards to the capital and liquidity risk variables, similar results are presented compared with results from random-effects models. Fintechs which have a higher level of capital and liquidity holdings level and meet legal requirements for these variables could obtain better performance. In more detail, all of them positively impact on ROE, LCR and CR show their positive impact at 1% and 5% significance level. Based on coefficient values, a 1% increase in LCR will lead to a 0.0033% positive impact on ROE, where CR shows a 0.3108% and T1 shows a 0.5045% positive impact on ROE. With regards to debt variables, the results show that both D/A and D/E have negative impacts at the 10% significance level on ROE. This result is consistent with our random-effects panel data regression models and traditional banks' results, which also presents the same results. With the coefficient values, a 1% increase in D/A will lead to a 0.1855% decrease in ROE, and a 1% increase in D/E will lead to a 0.0003% decrease in ROE. Thus, the importance of D/A is seen, which is proved by its higher coefficient value. This suggests that managers should consider more on D/A when managing risks.

With regards to operational risk variables, both variables also show significantly negative impacts on ROE, where the ORP shows a 10% significance level and C/I shows a 1% significance level. With regards to coefficient values, a 1% increase in ORP will lead to a 0.0285% negative change and C/I shows a 0.1966% negative impact. Similar to GMM estimates shown in fintechs' ROA, together with control over particular operational risks, UK fintechs also need to control their overall costs and increase their operational efficiency to obtain better performance. With regards to reputational risk variables, consistent results are shown compared with random-effects estimates for Chinese fintechs and GMM estimates for UK traditional banks. BVC also shows a positive impact on ROE, which suggests that increased reputation could help fintechs achieve better performance.

Finally, similar to the random-effects estimates for ROE, there is evidence of a positive relationship between size and ROE performance. At the 10% significance level, a 1% increase of fintechs' ln(asset) will lead to a 0.0706% increase of fintechs' ROE, which suggests that increasing size tends to result in better performance. In addition, similar to the results shown in random-effects estimates and unlike traditional banks, fintechs' ROE coefficient values do not show ten times larger than fintechs' ROA coefficient values. The possible reason could be that their ROA and ROE are not stable, as they are still developing. When they run long enough, the results may tend similar to traditional banks.

	Estimations	
	Traditional banks	Fintechs
Intercept	0.4675	-2.0946
One period lag of EPS	0.3522*	0.2714
Non-performing loan ratio	-1.8189**	-5.1854*
Net Charge-off rate	-1.9284	-11.1896
Total loan loss ratio	-0.3169*	-2.6007**
Value at risk	-0.0056*	-0.0368**
Liquidity coverage ratio	0.1393*	0.0388
Current ratio	0.2849	0.1149***
Tier 1 capital ratio	0.6655**	0.5563*
Debt-to Asset ratio	-0.2549*	-0.7548
Debt-to-Equity ratio	-0.1732*	-0.0013**
Brand value change %	0.6290	0.0597*
Operational risk %	-0.1077**	-0.9165***
Ln(Asset)	0.1378**	0.3571***
Cost-to-Income ratio	-0.0748*	-0.5293***
F-test	787.2***	308.0***
Sargan Test (p-value > χ^2)	39.1(0.465)	21.1(0.855)
AR(1)	z = -2.97 p-value = 0.00	z = -3.1 p-value = 0.00
AR(2)	z = -0.52 p-value = 0.60	z = -0.65 p-value = 0.52
No. of Obs.	70	30

Table 4.28 GMM estimation results (EPS, UK)

Notes: *, **, ***represent significant at 10%, 5% and 1% respectively.

Sargan test is the test for over-identifying restrictions in GMM dynamic model estimation.

AR(1) and AR(2) are Arellano-Bond test that average autocovariance in residuals of order 1 and 2 is 0 (H_0: no autocorrelation).

Finally, we are interested in observing whether the stock market's bank performance depends on managing different types of risks. The GMM estimates are applied to show coefficients and provide these results with EPS in Table 4.28.

For traditional banks, similar to GMM for traditional banks in ROA and ROE, the F-statistics show the significance of the variables, the Sargan test shows there is no evidence of over-identifying restrictions, and the AR tests show the estimates of independent variables are consistent. With regard to lagged dependent variables, although it is not significant, the coefficient of the lagged EPS shows the dynamic character of the model specification. δ takes a value of 0.3522 when performance is measured by EPS. This result also suggests that UK traditional banks' performance seems to persist in a relatively competitive market structure in EPS.

Turning to the other independent variables, the results here for the dependent variables are consistent with our random-effect panel data regression models. Firstly, credit risk variables have negative impacts on EPS. This suggests that higher credit risks lead to poor EPS for UK traditional banks. In details, NPL and LoanR significantly negatively impact the EPS at the 5% and 10% level, respectively. In these credit risk variables, the NCO has the largest coefficient number, a 1% increase of the NCO will lead to a 1.9284% decrease of the EPS where NPL and LoanR could lead to 1.8189% and 0.3169% decrease, representatively. Similar to random-effects models, NPL shows its importance in credit risk management based on the highest significance level together with its relatively high coefficient value. With regards to market risk variables, VaR has a significant negative impact on EPS at the 10% significance level which is similar to the results from random-effects estimates. Thus, in order to increase the bank's EPS, managers should control the VaR relatively low.

Regarding the capital and liquidity risk variables, consistent results also show in GMM compared with random-effects that all three variables positively influence the bank performance. In more detail, LCR and T1 show their positive impact at 10% and 5% significance level. It is not the same to show in random-effects estimates where CR and T1 are significant at the 5% and 1% significance level. This suggests that the importance of T1 during capital risk management, as T1 shows its significance in both models. Based on coefficient values, a 1% increase in LCR will lead to a 0.1393% increase of EPS, where CR shows a 0.2849% and T1 shows a 0.6655% increase of EPS. The results further indicate the importance of its higher coefficient value. Managers should follow the regulation requirements (e.g. Basel Accords) and increasing the capital holding level could help banks increase their performance. We further notice that the debt level variables are significantly negative related to EPS, where both of them are significant for EPS at the 10% level. In more detail, a 1% decrease in D/A will lead to a 0.2549% increase in EPS where D/E shows 0.1732% influence in EPS. Similar to the results from random-effects, the GMM results suggest that a lower debt level could help banks to receive better performance.

With regards to operational risk variables, GMM also provides results consistent with our random-effects panel data regression models. Both ORP and C/I affect EPS significantly and negatively at the 5% and 10% level. Based on the coefficient values, a 1% decrease of ORP or C/I will lead to a 0.1077% or 0.0748% increase in EPS. As both variables show their significance, managers in the UK traditional banks should control their operational risks during the business, especially in the stock market. For reputational risk variables, BVC shows a positive impact on EPS, where a 1% increase in BVC will lead to a 0.629% increase in their EPS. Although BVC is not significant in the EPS model, the result still suggests an increasing reputation could help bank increase EPS performance. Finally, the bank size significantly positive impacts bank performance at the 5% significant level for EPS. With a 1% increase in ln(asset), the UK traditional banks' EPS will increase 0.1378%.

For UK fintechs, The F-statistics show the significance of the variables. The Sargan test shows there is no evidence of over-identifying restrictions. The AR tests show that the estimates of independent variables are consistent. For the lagged dependent variable, the significant coefficient of the lagged EPS confirms the dynamic character of the model specification. δ takes a value of approximately 0.2714, which suggests that the performance of the UK fintechs seems to persist to a relatively competitive extent in EPS.

Estimates for the independent variables show results for EPS consistent with our random-effects panel data regression models. Firstly, all credit risk variables have negative impacts and the coefficient values of these variables are larger than were obtained for traditional banks. In more detail, NPL and LoanR are significantly negative impacts on the EPS at 10% and 5% significance level. For coefficient values, a 1% increase in NPL will lead to a 5.1854% decrease in EPS, NCO shows a 11.1896% and LoanR shows a 2.6007% decrease in EPS. We could see that the coefficient values are larger than they showed in traditional banks like random-effects models. This confirms that credit risk hurts bank performance as in traditional banks, but that fintechs should be more concerned with these credit risk variables. With regards to market risks, VaR shows a significantly negative relationship with EPS at the 5% level, where a 1% decrease in VaR will lead to a 0.0368% increase in EPS. In addition, fintechs are more related to other markets and have a smaller market scale than UK traditional banks. Thus, they should take more care about market risks with their relatively weak market position in the financial system, especially in the stock market.

With regards to the capital and liquidity risk variables, similar results are presented compared with results from random-effects models. Fintechs which have a higher level of capital and liquidity holdings level and meet legal requirements for these variables could obtain better performance. All of them positively impact the EPS, where CR and T1 show their significance at the 1% and 10% significance level. Based on coefficient values, a 1% increase in LCR will lead to a 0.0338% positive change of EPS, where CR shows a 0.1149% and T1 shows a 0.5563% positive change to EPS. With regards to debt variables, the results show that both D/A and D/E have negative impacts on EPS, where D/E has a significant negative impact on EPS at the 5% significance level. This result is consistent with our random-effects panel data regression models, which also presents the same results that D/E has a higher significance level than D/A. With the coefficient values, a 1% increase in D/A will lead to a 0.7548% decrease in EPS, and a 1% increase in D/E will lead to a 0.0013% decrease in EPS. Thus, the importance of D/E is seen, which is proved by its higher significance level. This suggests that managers should consider more on D/E when managing debt level risks.

With regards to operational risk variables, both variables also show significantly negative impacts on EPS at the 1% level, where a 1% increase in ORP will lead to a 0.9165% decrease and C/I shows a 0.5293% negative impact. Similar to GMM estimates shown in fintechs' ROA and ROE, together with control over particular operational risks, managers also need to control their overall costs and increase their operational efficiency to obtain better performance. With regards to reputational risk variables, consistent results are shown compared with random-effects estimates and GMM estimates for both types of banks. BVC also shows a significant positive impact on EPS at the 10% significance level which suggests that every 1% increase in BVC could help fintechs achieve a 0.0597% increase in EPS performance. Finally, similar to the random-effects estimates for EPS, there is evidence of a positive relationship between size and EPS performance. At the 1% of significance level, a 1% increase of fintechs' ln(asset) will lead to a 0.3571% increase of fintechs' EPS, which suggests that increasing size tends to result in better performance.

In summary, Similar to China, the F-statistics show the significance of the variables. The Sargan test shows no evidence of over-identifying restrictions, and the Arellano-Bond test shows the consistency of our estimates for the independent variables.

For the UK's traditional banks, firstly, the significant coefficient of the lagged performance variables (ROA and EPS) confirms the dynamic character of the model specification. It suggests that the performance of the UK's traditional banks seems to persist. This implies that the UK's traditional banks have a relatively competitive structure. This shows the higher competitiveness of the UK traditional banks than the Chinese traditional banks.

For other independent variables, similar results are presented as shown in our random-effects panel data regression models. Firstly, the credit risk variables have negative impacts. This suggests that higher credit risks lead to poor performance. Moreover, NCO is not significant for any of the three dependent variables, which does not prove that the NCO is not important in credit risk management, but only shows the other two variables are more influential, and that NCO is not the key variable in credit risk management. Moreover, the values of the estimates are larger than were showed for Chinese traditional banks. This suggests that the UK traditional banks should be more concerned with these credit risk variables.

With regards to market risk (VaR), VaR has a significant negative impact on all three bank performance variables. This suggests that higher market risk could decrease the performance of the UK's traditional banks. However, it shows a significant positive impact on ROE in the panel data regression models. As we tested that there is no endogeneity problem in the dataset, the difference here suggests that the UK traditional banks should be concerned more with market risks. As the results for the other two dependent variables are consistent, the UK traditional banks should keep VaR at a reasonable level and reduce the risk if possible, to achieve better performance. Next, with regards to the liquidity, capital and debt level variables, consistent results are shown compared with our random-effects panel data regression models. The positive relationship between liquidity and capital holding level and bank performance and the debt level variables is negatively related to bank performance. This suggests that in order to achieve a better performance, the UK traditional banks should increase their liquidity and capital holding level, and reduce their debt level. Moreover, managers should consider their different significant levels when managing this type of risk and prioritise them to achieve a better performance.

With regards to the operational risk variables, similar to our panel data regression models, C/I shows a higher significant impact on the UK traditional banks than in China. This suggests that together with concerning themselves with their particular operational risks, UK traditional banks also need to increase their operational efficiency. In addition, a similar result is shown in the reputational risk variable. BVC shows a positive impact on bank performance, which means that increasing reputation could increase bank performance. As BVC is significant for ROA and ROE at the 1% and 10% levels, respectively. The importance of bank reputation is shown, and similar to China, UK traditional banks need to be concerned with reputation when managing bank risks. Finally, regarding bank size, the coefficient of bank size is significant and negatively impacts ROE but positively on ROA and EPS. This result is consistent with the results obtained from our panel data regression models. With its significance for all three performance variables, UK traditional banks need to maintain their asset levels and find a balanced point to achieve better performance.

For the UK fintechs, the significant coefficient of the lagged performance variables

(ROA and ROE) confirms the dynamic character of the model specification. It suggests that the performance of the UK's fintechs seems to persist, and shows that they have a relatively competitive structure. Similar to the UK traditional banks, the competitiveness of fintechs in the UK is also higher than in China.

For other independent variables, consistent results are presented with our panel data regression models. Firstly, all credit risk variables have negative impacts, and at least two of them are significant. In particular, LoanR shows its significance for all three dependent variables. Managers, therefore, need to consider it more when managing credit risks. Moreover, the values of estimates are larger than was shown in traditional banks. This confirms that higher credit risks would reduce bank performance, and that fintechs should be more concerned about these credit risk variables than traditional banks. With regards to market risks, VaR shows results consistent with our panel data regression models. Unlike Chinese fintechs, there is a positive relationship between VaR and ROA and ROE and a negative relationship between VaR and EPS. This shows the complexity of market movements and the higher impact of market risk in the UK. Thus, UK fintechs should monitor market changes and find a balanced point of VaR to achieve better performance.

With regards to the capital and liquidity risk variables, similar results are obtained. Fintechs which have a higher level of capital and meet legal requirements in liquidity and capital holding level could achieve better performance. With regards to debt level variables, both of them show a negative relationship with bank performance. This suggests that a lower debt level could help UK fintechs to achieve a better performance. Thus, prioritising these variables in risk management based on their estimated values and significance could help managers achieve better efficiency and performance. With regards to operational risk variables, similar to the findings from the panel data regression models, the UK fintechs should be concerned to control particular operational risks and overall costs which could help them increase their operational efficiency and achieve a better performance. Concerning the reputational risk variables, BVC shows a positive impact on performance, which suggests that increased reputation could help fintechs reach better performance. However, as BVC is only significant for EPS at the 10% level, this suggests that BVC could influence bank performance but is not as a critical variable. Finally, similar to the Chinese fintechs, there is evidence of a positive relationship between size and performance, which suggest that increasing size tends to lead to better performance.

4.3.8 Summary

This section analysed 22 UK banks and listed them as two types (11 traditional banks and 11 fintechs). Firstly, we applied figure comparisons between the traditional banks and fintechs. Then, descriptive statistics, stationarity, multicollinearity, heteroscedasticity and endogeneity tests were presented and analysed. At last, by using ROA, ROE, and EPS as dependent variables, we employed panel data regression models and GMM to study the impact of different types of risks on both types of banks' performance. Moreover, as we used random-effects estimates to build a generalised model for the dataset. We did not need to add time- or individual- influence factors in the analysis, as they already be analysed through R^2.

The overall conclusions were consistent with the Chinese analysis, which was that improving different bank risk management could help the UK banks achieve more successful performance. Prioritising these risks could be a possible solution. For traditional banks, more attention should be paid to capital and liquidity risk, than to operational risks, credit risks and market risks. Meanwhile, the UK traditional banks should keep their size and reputation at a safe level. Fintechs, on the other hand, need to be more concerned about their credit risk, then pay attention to liquidity and capital risk and operational risk to an equal degree. Also, they must stay alert to market movements and then improve their asset level and reputation. Based on the findings in this section, managers of traditional banks and fintechs could use these estimates to manage different types of risks and use historical data to estimate future performance. Therefore, managers could know the influence level of different types of risks and variables by prioritising these risks. They could further provide a more efficient strategy when managing risks. In addition, managers could estimate their future performance through our models and set risk management targets. Moreover, through our models, managers could better understand their competitors, which could help them avoid some mistakes or improve some advantages through management.

At the same time, investors and shareholders in the UK could also benefit from our models. By finding the relevant variables from banks/fintechs official website or any legal ways, investors and shareholders can receive different results based on the bank type. This could help them know if a bank/fintech develops or which bank/fintech is better to invest in these days. Similarly, policymakers and governments in the UK could also benefit from our models. Instead of investing in banks/fintechs, they can find banks/fintechs perform better or worse than others which can help them keep their eyes on these banks/fintechs and support or shut down these banks/fintechs. Moreover, through our models, policymakers and governments can understand the general situation for different bank types, which can help them make more targeted regulatory requirements based on bank type. More discussion could be found in Chapter 6.

Differences and similarities were listed for the UK traditional banks and fintechs, as well as general similarities and difference between the UK banks and Chinese banks. Based on the process in this section, the following section applies our analysis to the Australia dataset.

4.4 Data analysis, results and discussion for Australia

In the previous sections, the risks influencing China and the UK banks' performance were identified for traditional banks and challenger banks/fintechs. In order to have a comprehensive result, this thesis will also present results for Australia following the same pattern as China and the UK. Similarly to Sections 4.2 and 4.3, this section also organised as follows: 1. Figure comparisons; 2 Descriptive statistics; 3. Panel-data unit-root tests (Fisher's type); 4. Correlation matrix and variance influence factors (VIF); 5. White’s test, F-test, Lagrange Multiplier Test and Durbin-Wu-Hausman (DWH) test; 6. Panel data regression models (random-effects type); 7. GMM estimates; 8. Summary.

4.4.1 Comparisons between Australian traditional banks and fintechs

Comparisons between Australian traditional banks and fintechs for bank performance and risk management are presented in Figures 4.15 to 4.21. Figure 4.15 shows all three performance variables for the Australian traditional banks and fintechs. With regards to ROA, similar to the profitable situation of Chinese traditional banks, the whole sample of Australian traditional banks achieved a positive ROA. Moreover, Australian traditional banks showed signs of stability with a slightly decreasing trend. With a similar range to Chinese traditional banks, the overall ROA performance showed similar results to Chinese traditional banks. At the same time, as there was no negative ratio of ROA, suggesting a better ROA performance than the UK traditional banks. On the other hand, for fintechs, ROA presented a similar situation to China and the UK fintechs. Some of the fintechs started with negative values and increased over the years to reach positive values. Some of them performed with a stable trend to keep their operations smooth. Even though volatility existed in ROA, the general trend was of growth for Australian fintechs. Similar to results in China and the UK, the ROE of Australian banks presented a similar trend to ROA.

With regards to EPS, Figure 4.15 only presented traditional banks/fintechs, which already joined the share market. Most Australian traditional banks presented a stable trend, and some had signs of a slightly increasing trend with volatility. Moreover, most of the EPS values stayed positive, which indicates a profit-making operation for Australian traditional banks. With higher values and more positive earnings, the EPS performance of Australian traditional banks showed a relatively better situation than the other two countries. For fintechs, as more fintechs joined the share market in Australia than China and the UK, Australian fintechs provided a better view of fintechs' performance in the share market. Generally, the overall performance stayed at an acceptable level. Most of the fintechs showed a smooth trend, and others showed a volatile trend. In addition, we could see that there are outliers for fintechs' ROA and ROE. Indeed, these points have much lower values than others. This suggests that in the infant stage of fintechs operations, these fintechs could have negative returns at different levels, but after this stage, they survived and began to have positive returns. Therefore, authorities could give fintechs chances even support them pass this stage.

Traditional banks Fintechs

Figure 4. 15 Bank performance comparisons (Australia)

With regards to credit risk variables, most values of the three variables showed signs of stabilising trends for Australian traditional banks. However, some of them had a trend of slightly increasing during the investigated time period. This result suggests that Australian traditional banks have effective credit risk management. However, the result also suggests that efficiency might be reduced during these years. Moreover, Australian traditional banks had a lower value of maximum credit risk level compared with Chinese traditional banks. This also suggested that Australian traditional banks had smooth credit risk management during the investigated time period.

For fintechs, on the other hand, an increasing trend was shown clearly in all three credit risk variables. A similar reason could be applied as for the Chinese fintechs, which was that Australian fintechs had less choice with customers and the traditional banks were experienced in dealing with credit risk management. Moreover, extreme values existed in these credit risk variables, as shown in the UK. The outlier suggests that the credit risks are high at the end of 2015 for ChangeFinance. After this stage, the figure shows that ChangeFinance reduces its credit risk levels to the average. Thus, this situation is acceptable. Moreover, this suggests that we should give the fintechs more time to show their management ability. In addition, it still indicates that fintechs in Australia had worse performance in credit risk management than traditional banks. It also indicates, similar to the UK, that Australian fintechs performed relatively worse than Chinese fintechs in credit risk management.

Traditional banks Fintechs

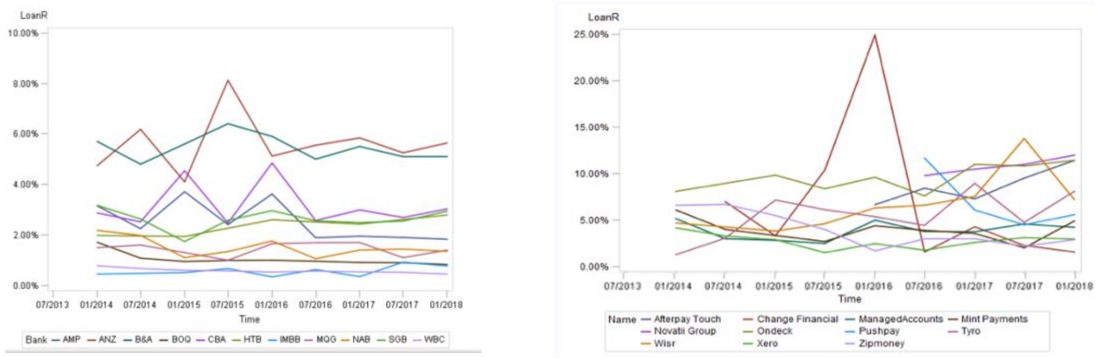


Figure 4.16 Credit risk variables comparisons (Australia)

With regards to market risk, VaR values in Australia showed a smaller range than in China and the UK. As the range of VaR in both types had a similar limit value, this showed that the market influence was relatively stable for the whole banking industry. Australian banks had less potential losses in the market and that the market influence was concentrated. Similar to China, Australia suffered less influence from the 2007-09 financial crisis (Docherty & Viort, 2014). With fewer impacts of market risks on Australian traditional banks, they operated with earning profits over decades. In addition, as the scale of fintechs was much less than traditional banks, a similar impact factor would lead to worse consequences. Fintechs might suffer more from market risks.

Traditional banks Fintechs

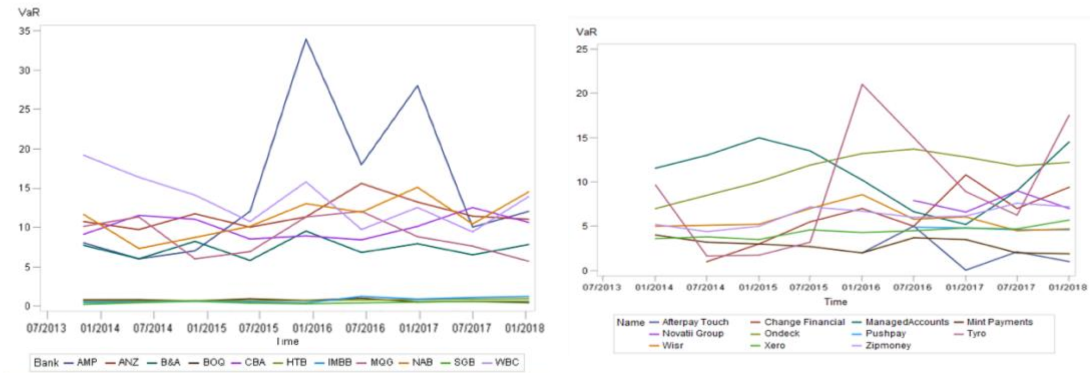


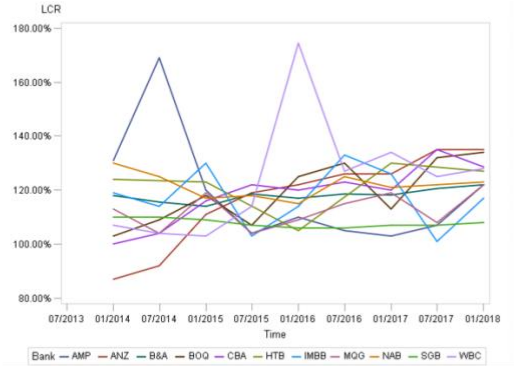
Figure 4.17 Market risk variable comparisons (Australia)

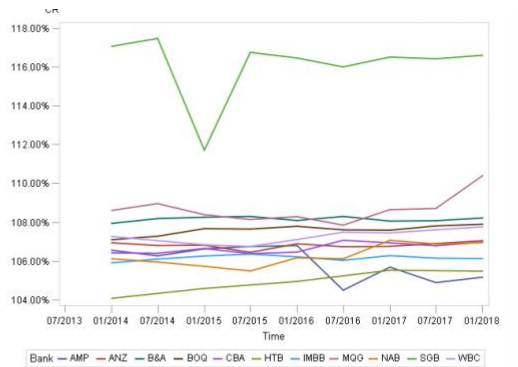
With regards to capital and liquidity risk, LCR, CR and T1 had a similar stable trend and passed the legal requirements of the Basel Accords, which shows that the liquidity and capital condition of the Australian traditional banks were smooth. However, unlike the other two countries, the liquidity and capital holding levels were not increased much during the investigated time period. This situation shows that Australian traditional banks have not prepared enough capital or liquidity for a future financial crisis like the other two countries, which might cause serious consequences when a crisis happens. On the other hand, LCR, CR and T1 had a similar increasing trend which shows that the liquidity and capital condition of Australian fintechs were developed. This result indicates a relatively better performance of fintechs than traditional banks, but not as good as the other two countries. However, not all of the Australian fintechs met the Basel requirement for T1. Therefore, these fintechs need to operate more carefully and try to add more tier one capital in the future. If they cannot meet the requirement, they have not enough capital to prevent their possible bankruptcy. Moreover, there is an outlier of LCR, CR and T1 in the Australian fintechs in Figure 4.18. It can be observed that the outlier has a much high value than other fintechs' data. The reason to explain this situation could be that the outlier fintech receives liquidity and capital investment during that period. As the outlier fintech still stays in the absorbing investment stage, the situation is acceptable. However, this situation should be temporary. If the fintech keep has too much liquidity and capital, the authority should investigate this fintech to find the reason.

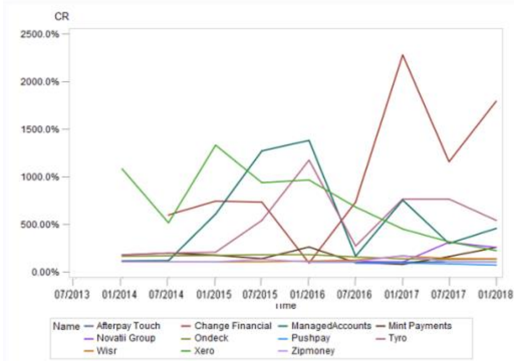
With regards to debt level variables, similar to Chinese traditional banks, Australian traditional banks had a stable trend for both D/A and D/E. This result indicates that Australian traditional banks controlled their debt level. On the other hand, the fintechs' D/A showed a different situation compared with Chinese and UK fintechs. The D/A values are volatile between fintechs. Generally speaking, Australian fintechs controlled their D/A with an overall stable trend. With regards to D/E, some of them showed negative values, like the Chinese fintechs, which had a negative net value situation. Moreover, there is an outlier in the Australian fintechs' figure. It shows a much higher D/E than others which proved its high debt level at the end of 2015. Because the outlier is the first point of the data entity, the possible reason could be that the fintech has low equity at the begging stage. As the D/E drops to the average values, this situation is accepted with a reducing trend with its development. Thus, Australian fintechs retain in a relatively high-risk situation, and they need to reduce their debt levels.

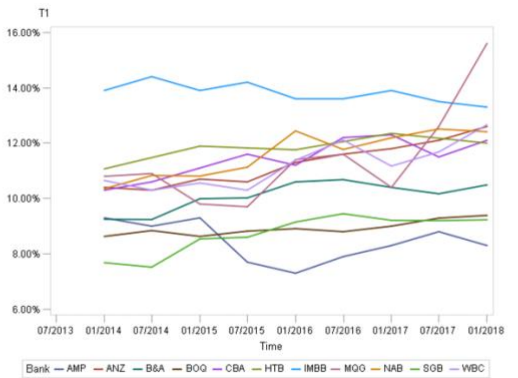
Traditional banks

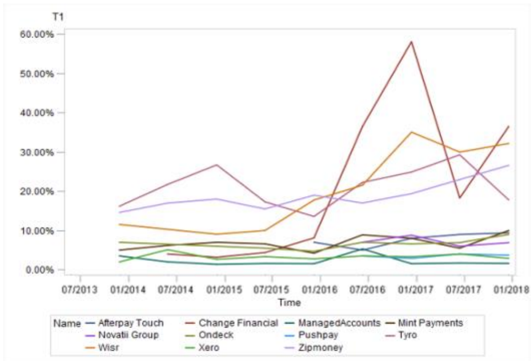
Fintechs

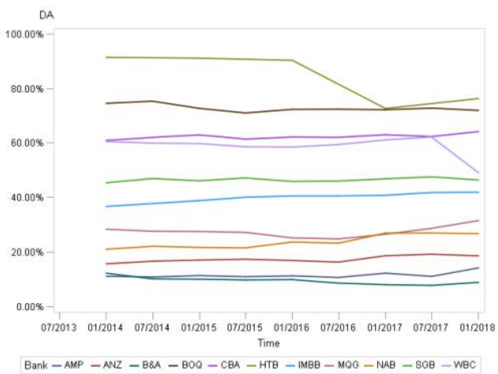


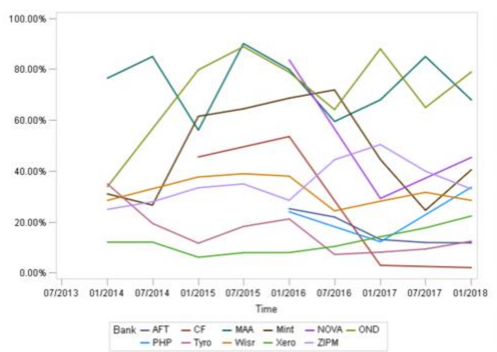












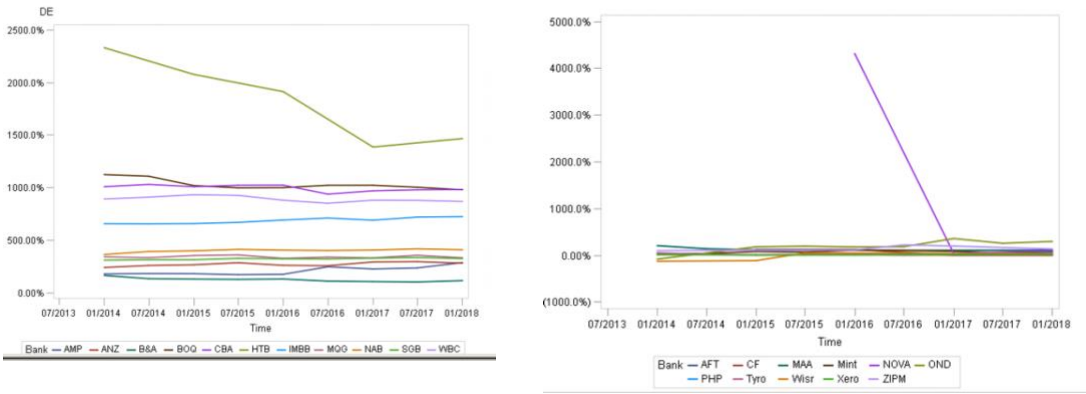


Figure 4.18 Liquidity and capital risk variable comparisons (Australia)

With regards to BVC, similar to the UK, the Australian traditional banks showed a volatile BVC, even though they had relatively good profitability during these years. Thus, traditional banks developed their reputation at a limited level. Australian fintechs also developed their reputation at a limited level. Thus, fintechs in Australia should learn from the other two countries to increase their reputations to attract more investors and customers. However, there is an outlier in the Australian fintechs' figure. It showed that in the middle of 2015, ChangeFinance increased its brand value much higher than other fintechs. As most Australian fintechs' BVC has a stable trend around zero, they need to increase their brand value to catch up with other countries.

Traditional banks Fintechs

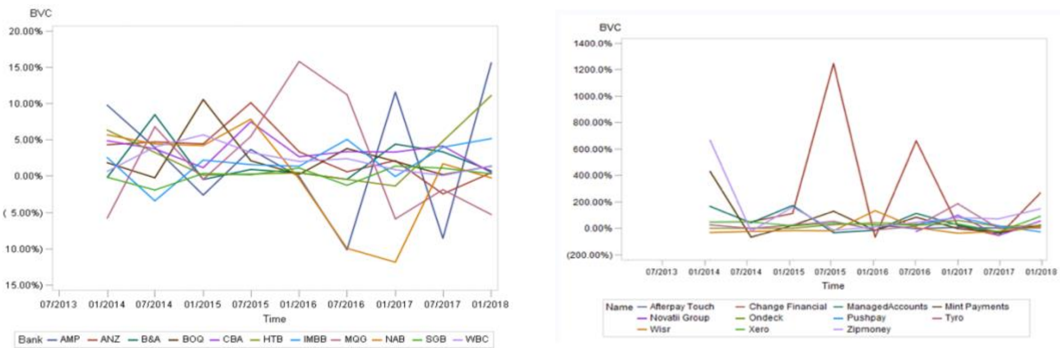
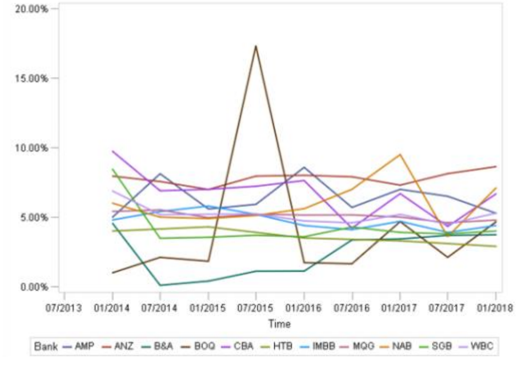


Figure 4.19 Reputational risk variable comparisons (Australia)

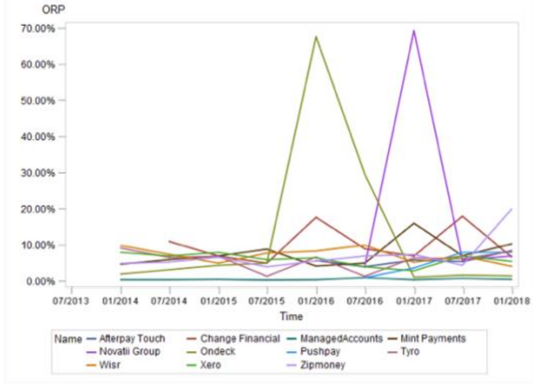
With regards to ORP, most Australian traditional banks stayed at a reasonable level, which was similar to Chinese traditional banks. In more detail, most of the ORP values were under 10%, which met the Basel requirement. However, similar to the UK, values over 15% exist, which indicates that bank costs were too high to cover the loss of occurring operational risks and might cause severe consequences for bank operations. In addition, ORP showed signs of slightly increasing trends for Australian fintechs. This result indicates that operational risks might influence future performance. Managers of traditional banks should be concerned by and reduce operational risks and costs. With regards to C/I, Australian traditional banks showed better performance than the UK with no values over 100%. However, as Chinese traditional banks had a lower range of values (45%), Chinese traditional banks had the best efficiency in operations of the three countries. Thus, this result shows that the operational efficiency of Australian traditional banks performed stables but needs to be further controlled.

Similar to the traditional banks, most of the ORP values for the Australian fintechs stayed at a reasonable level of less than 15%. However, similar to fintechs in the other two countries, extreme values exist. Two extreme examples are Ondeck and Novatti Group. Both of them have over 60% ORP values. As the values dropped to the average level after the outlier showed, this suggests that managers in these fintechs solved the problem and avoid high ORP keep occurring. However, as values over 15% exist, it suggests that these fintechs were in trouble with high costs to solve operational risk issues. Similar to fintechs in China and the UK, some of the Australian fintechs had over 100% C/I values, which suggested the cost of operation was higher than their income. This indicates the poor efficiency of these fintechs. Thus, both traditional banks and fintechs in Australia provided relatively poor performance in operational risk management.

Traditional banks



Fintechs



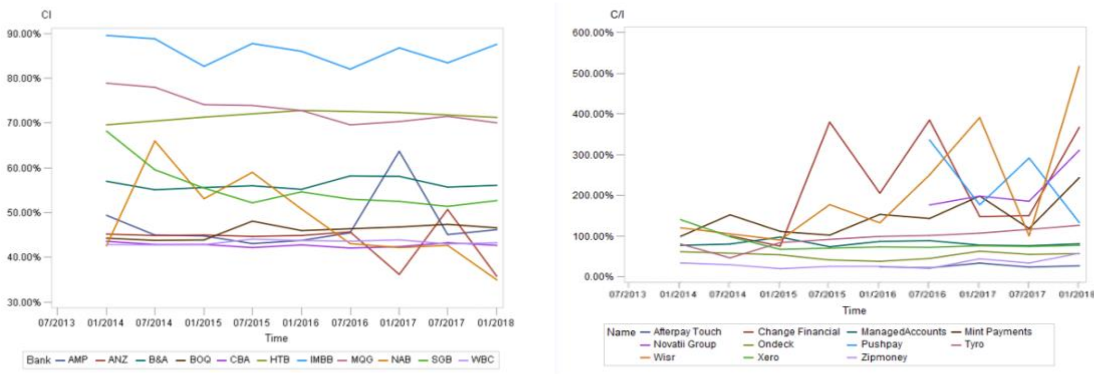


Figure 4.20 Operational risk variable comparisons (Australia)

Figure 4.21 shows the natural logarithm of the assets. Similar to the UK, the traditional banks of Australia had a stable trend which showed that they kept their asset during operations. Fintechs, on the other hand, had increased trends for their assets. This indicates their development during the investigated time period.

Traditional banks Fintechs

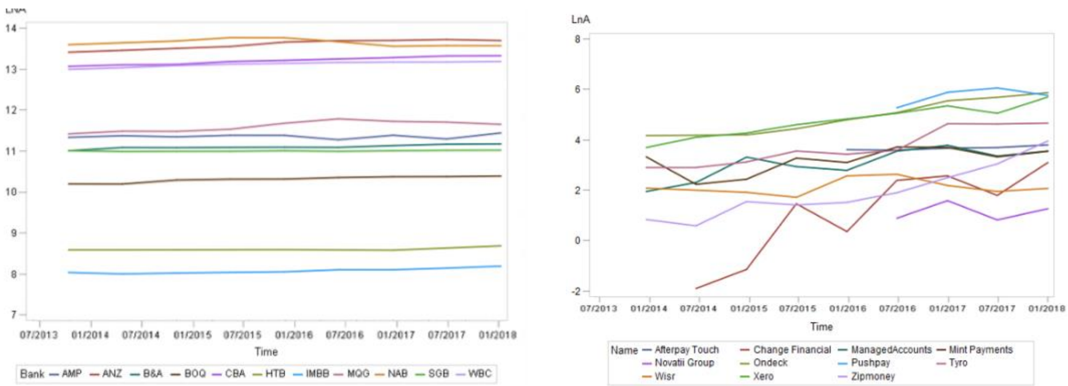


Figure 4.21 Bank size comparison (Australia)

In general, similar to Chinese banks, Australian banks performed relatively well during these years. However, both traditional banks and fintechs had shown signs of increasing trends in risk variables. Thus, Australian banks need to pay attention to risk management and be ready to react to future crises. If they failed to do so, serious trouble might appear during future financial crises.

4.4.2 Descriptive statistics

Tables 4.29 and 4.30 provide descriptive statistics for performance variables and risk variables based on types of bank. With regards to performance, the average ROA value was 0.8% for traditional banks, but -41.7% for fintechs, which suggests a worse than average performance than China. Moreover, for traditional banks, as no negative values existed in ROA, this shows that Australian traditional banks have a better performance than the UK. In addition, as fintechs in all three countries had a negative average value for ROA, this shows that fintechs did not make a profit on average. A similar situation happened with the average value of ROE. These results confirm the analysis from our figure comparisons above. With regards to EPS, the average EPS of traditional banks was $1.0938. This suggests that Australian traditional banks had better performance than China and the UK. For fintechs, Australian fintechs performed worse during the investigated time period than the other two countries with a -$0.05 average value. This suggests that Australian fintechs had relatively worse performance than excepted.

With respects to credit risk management variables, the average value of NPL was 0.82% in traditional banks, which stayed at a low level and was lower than traditional banks in China and the UK. NCO and LoanR were in a similar situation for Australian traditional banks. This suggests that, on average, Australian traditional banks had effective credit risk management. Fintechs had higher rate values than shown in Chinese fintechs. For example, the average value of NPL was 3.25%, which was higher than the average value of NPL in Chinese fintechs (2.2%). However, because of the results seen in Figure 4.16, both traditional banks and fintechs in Australia showed signs of increasing trends in credit risk variables. Thus, both types of banks need to check their credit activities and reduce risk values carefully.

Similar to China, the last financial crisis had limited impacts on the Australian banking industry. Reflecting on the market risks, VaR showed a similar risk level (the average value was 7.5952 for traditional banks and 6.8 for fintechs) as Chinese banks and a lower level than UK banks. The results showed that the Australian bank market was relatively stable, which provided good conditions for bank development. However, with a lower level of the market share that fintechs had, the impact of market risks will be more influential in fintechs.

Under liquidity and capital risk variables, traditional banks showed results that passed the Basel requirements on the average value, which was similar to traditional banks in

China and the UK. Moreover, because all traditional banks in Australia passed the 100% LCR value after 2015, this suggests that Australian traditional banks had a better liquidity situation than traditional banks in the other countries during the investigated time period. With regards to debt levels, Australian traditional banks provided higher average values in D/A and D/E than traditional banks in China. This suggests that there was room for improvement in traditional bank debt levels. For Australian fintechs, the average values of the liquidity and capital variables passed the Basel requirements. However, some of the fintechs did not meet the T1 requirement. For example, the minimum value of T1 was 1.36%. Moreover, the average values of D/A and D/E were lower than Chinese fintechs. This suggests that a relatively better debt situation for Australian fintechs. However, as negative D/E values existed (the minimum is -1.22), this indicates that negative equity existed in fintechs, which should be unacceptable. Therefore, regulators need to be more concerned about the fintechs which had negative values, monitoring their performance if they still perform poorly, and investigations should be applied to these fintechs.

For reputational risk variables, Tables 4.28 and 4.29 confirm the results shown in Figure 4.19. On average, traditional banks kept their brand value with a 2.1% average value, and fintechs developed their brand value with a 67.1% average value during the investigated time period. In addition, both traditional banks and fintechs in Australia had a lower average value in ln(asset) than in the UK, which suggests that they have a smaller size.

With regards to operational risk variables, ORP for the Australian traditional banks showed a higher average value of 5.19% than China (2.4%). This result suggests that traditional banks in Australia should learn from China to improve operational risk management efficiency. ORP for Australian fintechs showed a lower average value of 7.75% than the other two countries (China with 406%, 5.19% without extreme values and the UK with 11.38%). The Australian fintechs performed relatively better than fintechs in China and the UK. However, the average ORP value of the fintechs was still higher than traditional banks. This suggests that fintechs need to reduce operational risk issues to prevent future disasters. Moreover, in three countries, Australian traditional banks had a middle position with respects to their C/I average value, where the average value was 55.16% for Australia, 27.67% for China and 65.68% for the UK. This suggests that Australian traditional banks had a lower operational efficiency than Chinese traditional banks but a higher operational efficiency than the UK ones. For fintechs, the average C/I was 120%, which suggests that the operational efficiency is low. Similar to the other two countries, fintechs had poor operational efficiency as their costs were higher than their income. Thus, they need to cut their costs or improve their incomes to achieve higher efficiency.

Variable	Mean	Standard deviation	Maximum	Minimum
Return on asset	0.0080	0.0029	0.0170	0.0004
Return on equity	0.1177	0.0363	0.1880	0.0046
Earnings per share	1.0938	1.0029	4.143	-0.1100
Non-performing loan ratio	0.0082	0.0049	0.0180	0.0015
Net Charge-off rate	0.0075	0.0100	0.0600	0.0001
Total loan loss ratio	0.0245	0.0179	0.0812	0.0034
Value at risk	7.5952	6.2850	34.000	0.2100
Liquidity coverage ratio	1.1776	0.1290	1.7440	0.8700
Current ratio	1.0780	0.0294	1.1747	1.0408
Tier 1 capital ratio	0.1075	0.0175	0.1560	0.0730
Debt-to-Asset ratio	0.3951	0.2356	0.9139	0.0780
Debt-to-Equity ratio	5.9784	4.4063	23.3136	1.0438
Brand value change %	0.0210	0.0473	0.1580	-0.1185
Operational risk %	0.0519	0.0236	0.1730	0.0010
Ln(Asset)	11.5428	1.7751	13.7730	7.9990
Cost-to-Income ratio	0.5516	0.1463	0.8955	0.3500
Observations			95	

Table 4.29 Descriptive statistics (Australian traditional banks)

Variable	Mean	Standard deviation	Maximum	Minimum
Return on asset	-0.4170	0.5285	0.1112	-2.5870
Return on equity	-0.8127	1.1919	0.1580	-7.0545
Earnings per share	-0.0503	0.0929	0.1300	-0.4400
Non-performing loan ratio	0.0325	0.0316	0.2353	0.0010
Net Charge-off rate	0.0193	0.0159	0.0600	0.0010
Total loan loss ratio	0.0587	0.0376	0.2497	0.1280
Value at risk	6.7337	4.1363	21.0000	0.0500
Liquidity coverage ratio	2.8222	3.7302	22.5700	0.9000
Current ratio	3.7848	4.1370	22.8200	0.7200
Tier 1 capital ratio	0.1148	0.1056	0.5812	0.0136
Debt-to-Asset ratio	0.3849	0.2552	0.9010	0.0215
Debt-to-Equity ratio	1.3223	4.9327	43.1517	-1.2200
Brand value change %	0.6713	1.8021	12.4690	-0.6680
Operational risk %	0.0775	0.1074	0.6940	0.0030
Ln(Asset)	3.1775	1.5780	6.0490	-1.897
Cost-to-Income ratio	1.2041	1.0010	5.1700	0.193
Observations			82	

Table 4.30 Descriptive statistics (Australian challenger banks/fintechs)

Notes: Not all Australian traditional banks are listed, observations are 81 for EPS
Not all Australian challenger banks/fintechs are listed, observations are 72 for EPS.

Through examining the descriptive statistics, we conclude that Australian traditional banks' performance and risk management were relatively better than fintechs. However, both types of banks had higher risk potential, which might cause problems with their future performance. Thus, they were valuable to investigate to help them improve their performance in the future.

4.4.3 Panel data unit root test

Similar to China and UK, before applying the regression model, we apply a unit root test for panel data to test the stationarity of the data set at first. In more detail, Fisher-type unit root tests were implemented based on ADF tests to test the stationarity of the data. The null and alternative hypotheses are H_0 is that the data are non-stationary or have unit roots, and H_1 that the data are stationary or do not have unit roots. The results of the unit root based on bank type are shown in Table 4.31. The results show that all variables are stationary at the 1% level of significance. The null hypothesis for the variables is rejected, indicating that there is no evidence of unit root and the data are stationary.

	Traditional banks		Challenger banks/fintechs	
Variable	Statistics	P-value	Statistics	P-value
ROA	55.49	0.000	113.85	0.000
ROE	52.85	0.000	101.22	0.000
EPS	51.18	0.000	55.44	0.000
NPL	43.36	0.000	95.68	0.000
NCO	68.12	0.000	90.20	0.000
LoanR	61.30	0.000	96.29	0.000
VaR	53.48	0.000	95.21	0.000
LCR	45.78	0.000	85.98	0.000
CR	73.26	0.000	74.35	0.000
T1	45.97	0.000	81.20	0.000
D/A	44.57	0.000	79.93	0.000
D/E	53.60	0.000	75.76	0.000
BVC	67.47	0.000	82.56	0.000
ORP	58.70	0.000	84.84	0.000
Ln(Asset)	79.85	0.000	78.00	0.000
C/I	47.79	0.000	85.45	0.000

Table 4.31 Fisher's type unit root tests (Australia)

4.4.4 Correlation matrix and variance inflation factors

Tables 4.32 and 4.33 show the correlations of the explanatory variables for Australian banks based on bank types. Similar to the results from China and the UK, there was no two variables that had a correlation coefficient over 0.8. Thus, no multicollinearity problem exists. However, we could also see that there is some relatively high correlations (close to and over 0.7) that exist between independent variables in matrices showed above. Thus, we apply VIF for our dataset to double-check for multicollinearity problems. Table 4.34 presents the VIFs for all variables based on types of banks. Smilar to China and the UK, some variables show a relatively high VIF, which indicates their higher interaction with other independent variables, such as ln(asset)for traditional banks and D/A for fintechs. This indicates the importance of asset management for Australian traditional banks and debt management for Australian fintechs. As all VIFs are below 10, the results double-check the correlation matrix results and indicate that there are no issues of multiple correlation in this study.

	NPL	NCO	LoanR	VaR	LCR	CR	T1	D/A	D/E	BVC	ORP	Ln A	C/I
NPL	1												
NCO	-0.0773	1											
LoanR	0.1545	0.6836	1										
VaR	-0.0460	0.1766	0.1770	1									
LCR	-0.1880	-0.0489	-0.0572	0.0133	1								
CR	0.3159	-0.0516	0.0796	-0.3353	-0.2367	1							
T1	-0.4967	-0.0170	-0.1902	-0.0792	0.2324	-0.3639	1						
D/A	0.1217	-0.3368	-0.4636	-0.4163	0.0514	0.0276	0.0684	1					
D/E	0.0576	-0.2620	-0.3929	-0.3014	0.1169	-0.3182	0.2185	0.7907	1				
BVC	0.0741	0.1382	0.0670	0.0352	-0.0098	-0.1586	-0.0777	0.0173	0.0753	1			
ORP	0.0970	0.1549	0.0690	0.3848	-0.0418	-0.1637	0.0550	-0.1815	-0.0700	0.0375	1		
Ln A	-0.0004	0.3540	0.2923	0.6512	0.0847	-0.0285	-0.1017	-0.1508	-0.0793	0.0630	0.3766	1	
C/I	-0.2019	-0.2764	-0.2865	-0.4332	-0.1282	-0.0046	0.4307	-0.0814	-0.0700	-0.0397	-0.2306	-0.4312	1

Table 4. 32 Cross correlation matrix (Australian traditional banks)

	NPL	NCO	LoanR	VaR	QR	LCR	CR	T1	D/A	D/E	BVC	ORP	Ln A	C/I
NPL	1													
NCO	-0.0096	1												
LoanR	0.7616	0.4689	1											
VaR	0.0628	0.1361	0.1092	1										
QR	-0.2219	-0.2018	-0.2975	0.0093	1									
LCR	-0.2108	-0.1609	-0.2613	-0.0486	0.6860	1								
CR	-0.2595	-0.1641	-0.3158	0.1895	0.6253	0.5830	1							
T1	-0.1225	0.1128	-0.0578	0.0363	0.2599	0.2924	0.2095	1						
D/A	0.1704	-0.0028	0.1615	-0.1132	0.4263	0.4368	0.3170	-0.1031	1					
D/E	0.1037	0.0619	0.1096	0.1404	-0.3349	-0.3388	-0.2645	0.3081	-0.7314	1				
BVC	0.0307	-0.1091	-0.1091	-0.0276	0.1551	0.1793	0.0966	0.0710	0.1102	0.0738	1			
ORP	0.0958	0.1452	0.1918	0.0554	-0.0288	0.0086	-0.0865	0.0187	0.3738	-0.2087	-0.0053	1		
Ln A	-0.1508	0.0448	-0.1107	0.1989	-0.0055	0.0067	0.0205	-0.1772	-0.1897	-0.0560	-0.1026	-0.0186	1	
C/I	0.0832	0.1386	0.1367	-0.0893	0.1901	0.2237	0.1361	0.2262	0.3109	-0.0897	0.2815	0.0340	-0.0837	1

Table 4.33 Cross correlation matrix (Australian challenger banks/fintechs)

Variable	Traditional banks	Challenger banks/fintechs
NPL	2.585	3.248
NCO	4.246	4.574
LoanR	4.445	4.571
VaR	2.975	1.458
LCR	1.324	4.106
CR	4.317	4.387
T1	2.593	1.697
D/A	4.248	4.881
D/E	4.421	3.424
BVC	1.308	1.216
ORP	2.070	1.432
Ln(Asset)	4.940	1.473
C/I	3.266	1.418

Table 4.34 Variance inflation factors (Australia)

4.4.5 Tests for heteroscedasticity, endogeneity and model determination

Similar to China and UK, we tested heteroscedasticity for Australia, White's general heteroscedasticity test is employed and the results are shown in Table 4.35. The results of White's test show that heteroscedasticity is present. Since heteroscedasticity causes standard errors to be biased, after finding the proper static panel model, we used robust standard errors.

	Bank type	ROA model	ROE model	EPS model
		p-values		
White's test	Traditional banks	0.0000	0.0000	0.0000
	Fintechs	0.0000	0.0000	0.0000

Table 4.35 Tests for heteroscedasticity

Moreover, we tested the endogeneity of the Australia dataset through the DWH test. Table 4.36 show that we could not reject the null hypothesis (H_0: there is no endogeneity exist, and random-effects is more appropriate), we could see that there is no endogeneity problem for this study. Moreover, as mentioned in Section 4.2.5 and Section 4.3.5, we need to apply three tests to find the most appropriate approach to obtain our panel regression results. Table 4.36 shows the p-values of this test for the Australia dataset. The results show that we need to reject the null hypothesis of the F test and Lagrange Multiplier test (H_0: the pooled OLS is more appropriate). This suggests that models with fixed- and random-effects are more appropriate than pooled OLS with zero p-values for all dependent variables and bank types. All p-values are greater than 5% for all three dependent variables in the DWH test, so we cannot reject the null hypothesis. This suggests that random-effects models are suitable.

Test	Bank type	ROA model	ROE model	EPS model
			p-values	
F	Traditional banks	0.0000	0.0000	0.0000
	Fintechs	0.0000	0.0000	0.0000
LM	Traditional banks	0.0000	0.0000	0.0000
	Fintechs	0.0000	0.0000	0.0000
DWH	Traditional banks	0.1965	0.5112	0.3307
	Fintechs	0.4575	0.1223	0.3220

Table 4.36 Tests for determination the most appropriate approach for data analysis (Australia)

4.4.6 Panel data regression analysis

Based on the three dependent variables, we constructed six random-effects panel data regression models to test the influences of risk variables on the bank performance variables based on different bank types. The random-effects model estimation results are shown in Tables 4.37 to 4.39.

	Traditional banks		Fintechs	
	Estimations	Robust Std. Err	Estimations	Robust Std. Err
Intercept	0.0652	0.0204	-0.5213	0.1864
Non-performing loan ratio	-0.1614**	0.0735	-1.7167*	1.3951
Net Charge-off rate	-0.0752*	0.0613	-2.6275	1.9310
Total loan loss ratio	-0.0121*	0.0377	-2.2130*	1.2462
Value at risk	-0.0001***	0.0007	-0.0039*	0.0110
Liquidity coverage ratio	0.0008*	0.0022	0.0148*	0.0688
Current ratio	0.0093	0.0197	0.0127*	0.0226
Tier 1 capital ratio	0.0513**	0.0234	0.4778	0.5685
Debt-to Asset ratio	-0.0128***	0.0055	-0.4137***	0.1541
Debt-to-Equity ratio	-0.0006***	0.0003	-0.0036	0.0027
Brand value change %	0.0045***	0.0059	0.0792***	0.0211
Operational risk %	-0.0322**	0.0127	-0.0045	0.0872
Ln(Asset)	0.0002**	0.0003	0.1025***	0.0336
Cost-to-Income ratio	-0.0045	0.0039	-0.0119**	0.0431
R^2_{within}	0.6914		0.6547	
$R^2_{between}$	0.7337		0.6744	
$R^2_{overall}$	0.5582		0.3907	
No. of Obs.	95		82	

Table 4.37 Random-effects estimation results (ROA, Australia)

Note: *, **, ***represent significance at the 10%, 5% and 1% levels respectively.

The first dependent variable is ROA. With regards to credit risk variables, similar results have been shown for China and the UK. All credit variables have a negative influence on Australian traditional banks and fintechs. In more detail, all three variables (NPL, NCO and LaonR) have significant negative impacts on Australian traditional banks' ROA at the 5%, 10% and 10% significance level, respectively. The NPL has the largest coefficient number, a 1% increase in the NPL will lead to a 0.1614% decrease in the ROA where NCO and LoanR can lead to a 0.0752% decrease and a 0.0121% decrease, representatively. When managing credit risks, managers should consider more on the NPL with its higher significance levels and coefficient value. This suggests that Australian traditional banks should be more concerned about credit risk management as all three variables are significant and have a slightly increasing trend in these credit risk variables shown in Figure 4.16. For fintechs, consistent results were also seen. NPL and LoanR show a significant negative impact on ROA at the 10% level.

With regards to coefficient values, the NCO has the largest coefficient number, a 1% increase of the NCO will lead to a 2.6275% decrease of the ROA where NPL and LoanR could lead to 1.7167% and 2.213% decrease, representatively. Thus, based on the significance level and coefficient value, managers in Australian fintechs should focus more on LoanR with its relatively higher levels when managing credit risks. Moreover, as higher estimates are seen for fintechs, credit risks have stronger influences for fintechs than traditional banks.

With regard to VaR, it has a significant negative impact on both traditional banks and fintechs. This result suggests that market movement has a more significant impact on Australian banks than Chinese banks, as VaR significantly impact ROA for Chinese traditional banks. Contrary to the results from the UK fintechs, VaR also negatively influence the ROA of Australian fintechs, which suggests that even some market movement could bring profits, while losses from the market risk occur more for Australian fintechs. In more detail, a 1% increase in VaR will lead to a 0.0001% decrease in traditional banks' ROA and a 0.0039% decrease in fintechs' ROA.

For the liquidity and capital risk variables, consistent results are achieved for both types of banks. LCR and T1 show significant positive impacts on traditional banks' ROA at 10% and 5% significant level, respectively. For fintechs, LCR and CR show significant positive impacts on ROA at the 10% significance level. For coefficient values, a 1% increase in LCR will lead to a 0.0008% increase in ROA, where CR and T1 could lead to 0.0093% and 0.0513%, representatively, for Australian traditional banks. For fintechs, a 1% increase in LCR will lead to a 0.0148% increase in ROA, where CR and T1 could lead to 0.0127% and 0.4778%, representatively. This shows that increasing liquidity coverage, current assets and tier one capital holding percentage could help both types of banks to improve ROA performance. As T1 has the highest significance level and the coefficient value for Australian traditional banks, managers should take extra care about T1. For Australian fintechs, as LCR has the highest significance level combined with a relatively high coefficient value, managers should take extra care about LCR. With regards to debt level variables, D/A and D/E show significant negative impacts on ROA at the 1% significant level for traditional banks and only D/A shows a significant negative impact on fintechs. With regards to coefficient values, a 1% increase in D/A or D/E will lead to a 0.0128% or 0.0006% decrease in ROA for traditional banks. In contrast, a 1% increase in D/A or D/E will lead to a 0.4137% or 0.0036% decrease in ROA for fintechs. This result indicates that a reduced debt level could help both types of banks improve ROA performance. Moreover, as both variables are significant for traditional banks, managers should pay more attention to debt level when managing risks. For fintechs, managers could pay more attention to D/A as it has a higher significance level. In summary, together with the findings shown in Section 4.4.1, Australian banks should pay more attention to this type of risk, because of their higher risk management failure potential.

Next, with regards to reputation risks, BVC shows a significant positive impact on ROA for both types of banks at the 1% significance level. Moreover, a 1% increase in BVC will lead to a 0.0045% increase in traditional banks' ROA and a 0.0792% increase in fintechs. Similar to Chinese banks, this result shows that the more significant an improvement of the bank brand value, the better the ROA will be. Moreover, similar to the UK banks, there is evidence of a significant positive relationship between bank size and ROA for traditional banks and fintechs, which suggests that increasing size tends to give higher ROA. In more detail, ln(asset) shows its significance at the 5% level for traditional banks and the 1% level for fintechs. A 1% increase in ln(asset) will lead to a 0.0002% increase in traditional banks' ROA and a 0.1025% increase in fintechs' ROA.

Finally, with regards to operational risk, both variables show their negative impact on both types of banks'/fintechs' ROA. ORP is a significant negatively influencing factor on the traditional banks' ROA. When issues related to operational risks occur, traditional banks decrease their ROA performance. Moreover, a 1% increase in ORP will lead to a 0.0322% decrease in traditional banks' ROA and a 0.0045% decrease in fintechs' ROA. Concerning C/I, this shows a significant negative impact on Australian fintechs, which suggests that the lower the efficiency of operations, the lower the ROA that will be achieved. Moreover, a 1% increase in C/I will lead to a 0.0045% decrease in traditional banks' ROA and a 0.0119% decrease in fintechs' ROA. Thus, managers for both types of banks need to control issues related to the probability of occurred operational risks and reduce the overall cost of operations to achieve a better ROA performance. As C/I shows a higher significance level coefficient value for fintechs, fintechs' managers should pay more attention to this variable than traditional banks during operational risk management. For a similar reason, managers for traditional banks should concern more about ORP.

Similar to China and UK, besides interpreting variables, we looked at the R^2 for our ROA models. R^2(within) shows a 69% variation within one traditional banks over time and a 65% variation within one fintech over time. R^2(between) shows 73% variation between traditional banks and 67% variation between fintechs. R^2(overall) shows 55% for traditional banks and 39% for fintechs. We could find out that traditional banks have slightly higher R^2s, which indicate higher variation was presented in traditional banks.

	Traditional banks		Fintechs	
	Estimations	Robust Std. Err	Estimations	Robust Std. Err
Intercept	-0.7463	0.2252	-0.5546	0.4478
Non-performing loan ratio	-1.9657***	0.8126	-1.1539*	1.9445
Net Charge-off rate	-0.5286*	0.6722	-5.2338*	2.1428
Total loan loss ratio	-0.3678*	0.4127	-2.9929**	1.9008
Value at risk	-0.0006**	0.0008	0.0115	0.0317
Liquidity coverage ratio	0.0197	0.0242	0.0105*	0.1997
Current ratio	0.4364***	0.2179	0.0268	0.0686
Tier 1 capital ratio	0.8019***	0.2517	0.7972**	1.4965
Debt-to Asset ratio	-0.0452***	0.0609	-1.2218***	0.3801
Debt-to-Equity ratio	-0.0056*	0.0032	-0.0180**	0.0069
Brand value change %	0.1467**	0.0648	0.1235**	0.0620
Operational risk %	-0.0145**	0.1393	-0.1632	0.1134
Ln(Asset)	0.0527***	0.0034	0.0184*	0.0830
Cost-to-Income ratio	-0.0170	0.0426	-0.0266**	0.0803
R^2_{within}	0.6177		0.4506	
$R^2_{between}$	0.6472		0.5082	
$R^2_{overall}$	0.5176		0.2153	
No. of Obs.	95		82	

Table 4.35 Random-effects estimation results (ROE, Australia)
Note: *, **, ***represent significant at 10%, 5% and 1% respectively

For ROE, the results are similar. Firstly, all credit risk variables have significant negative impacts on ROE, where they have higher impacts on the fintechs. As all three variables show the significance of both types of banks, managers should focus more on their significance levels and the coefficient values. As a 1% increase in NPL will lead to a 1.9657% decrease in ROE at the 1% significance level, managers should concern more on NPL for Australian traditional banks. For fintechs, managers should consider more on LoanR as it has the highest significance and a relatively high coefficient value. Next, with regards to market risk, VaR presents a similar result to the Chinese results. It shows a significant negative impact on traditional banks at the 5% significance level but a positive impact on fintechs. A 1% increase in VaR will lead to a 0.0006% decrease in traditional banks' ROE and a 0.0115% increase in fintechs' ROE. The possible reason could be that market movement may bring opportunities for fintechs to earn some returns. As the estimate for fintechs is not significant, fintechs still need to control market risk levels to ensure a performance improvement.

Thirdly, with regards to liquidity and capital risk variables, consistent estimates are seen. For traditional banks, CR and T1 have significant positive impacts on ROE at the 1% significant level. For fintechs, LCR and T1 have significant positive impacts on ROE at 10% and 5% significance levels. In addition, with regards to coefficient values, T1 shows the highest value for both types of banks. For traditional banks, a 1% increase in T1 will lead to a 0.8019% increase in traditional banks' ROE and a 0.7972% increase in fintechs' ROE. Moreover, with regards to debt level, D/A and D/E significantly negatively influence ROE for both traditional banks and fintechs. With regards to coefficient values, D/A shows a higher impact than D/E for both types of banks. Similar to Chinese banks, in order to have a better performance in ROE, Australian banks need to keep liquidity and capital holding percentages at a healthy level and reduce debt to a reasonable level. In addition, as these variables show different levels of significance and coefficient values, managers should prioritise these variables based on their significance level and estimation values when managing liquidity and capital risks. Based on the coefficient values and significance levels, both types of Australian banks should concern more about T1 and D/A.

With regards to reputational risks and bank size, similar to the results obtained from ROA, BVC and ln(asset) have a significant positive impact on ROE for both types of bank. This means that increase brand value and bank size could help Australian banks to improve their performance. Finally, concerning operational risk variables, the results are consistent with the other two countries. Both variables have negative impacts on ROE. In more detail, OPR shows a significant negative impact on ROE for traditional banks at the 5% significance level, and C/I shows a significant negative impact on ROE for fintechs at the 5% significance level. With regards to coefficient values, a 1% increase in ORP will lead to a 0.0145% decrease in ROE for traditional banks and a 0.1632% decrease for fintechs. A 1% increase in C/I will lead 0.0170% decrease in ROE for UK traditional banks and a 0.0266% decrease for the UK fintechs. This suggests that traditional banks should pay more attention to particular issues of operational risks, with OPR having a higher significance level and coefficient value. Fintechs should concern the overall operational costs and operational efficiency together. This confirms that keeping bank operations smooth and decreasing operational issues and costs could help Australian banks to improve their ROE.

Similar to China and UK, besides interpreting variables, we looked at the R^2 for our ROE models. R^2(within) shows a 61% variation within one traditional banks over time and a 45% variation within one fintech over time. R^2(between) shows 64% variation between traditional banks and 51% variation between fintechs. R^2(overall) shows 51% for traditional banks and 21% for fintechs. We could find out that traditional banks have higher R^2s, which indicate higher variation was presented in traditional banks.

	Traditional banks		Fintechs	
	Estimations	Robust Std. Err	Estimations	Robust Std. Err
Intercept	-8.3585	10.9193	0.0193	0.0524
Non-performing loan ratio	-65.9641**	33.9845	-3.3560*	2.2511
Net Charge-off rate	-8.1478*	17.2592	-3.2227	2.4406
Total loan loss ratio	-13.4135	12.6794	-1.0387*	2.1490
Value at risk	-0.0142*	0.0184	-0.0030*	0.0035
Liquidity coverage ratio	0.1536*	0.5338	0.0061**	0.0205
Current ratio	7.2401**	9.8203	0.1816	0.0194
Tier 1 capital ratio	12.0902*	9.1940	0.2002*	0.1690
Debt-to Asset ratio	-2.0723*	3.3781	-0.0180	0.0419
Debt-to-Equity ratio	-0.0683	0.2244	0.0012***	0.0008
Brand value change %	0.8254**	1.3640	0.0015*	0.0088
Operational risk %	-0.1201***	3.1666	-0.1495**	0.1145
Ln(Asset)	0.3414***	02606	0.0185**	0.0098
Cost-to-Income ratio	-0.2639**	1.3179	-0.0065	0.0129
R^2_{within}	0.6158		0.5901	
$R^2_{between}$	0.7126		0.6782	
$R^2_{overall}$	0.5605		0.3309	
No. of Obs.	81		72	

Table 4.39 Random-effects estimation results (EPS, Australia)

Note: *, **, ***represent significance at the 10%, 5% and 1% levels respectively.

Finally, we observed how different types of risk variables influence the EPS of selected listed Australian banks. Our results show some similarity to the above results. For examples, all credit risk variables impact negatively on the EPS. In more detail, managers should pay more attention to variables that show a higher significance level, such as NPL and NCO for traditional banks and NPL and LoanR for fintechs. Managers should also focus on the coefficient values. As a 1% increase in NPL will lead to a 65.9641% decrease in EPS for traditional banks and a 3.3560% decrease in EPS for fintechs, managers should concern more on NPL for both types of Australian banks. Secondly, market risk also has a significant negative influence on both types of Australian banks at the 10% significant level. A 1% increase in VaR will lead to a 0.0142% decrease in traditional banks' EPS and a 0.003% decrease in fintechs' EPS. This suggests that reducing VaR could help them to achieve better performance.

Thirdly, with regards to the liquidity and capital risk variables, similar results are seen. LCR, CR, T1 and D/A have significant impacts on EPS for traditional banks and LCR, T1 and D/E have significant impacts on EPS for fintechs. With regards to coefficient values, T1 shows its highest impact in three capital and liquidity variables and D/A shows a higher impact than D/E for both types of banks. These results suggest that similar to the other two countries' results, higher liquidity and capital holding percentages combined with a relatively low and stable debt level would help banks and fintechs perform better in EPS. Managers could manage these risks according to their different significance levels and estimated values. Fourthly, similar to the results for ROA and ROE, BVC and ln(asset) also have significant positive influences on EPS for both types of bank. This suggests that a better bank reputation and a higher size level could help traditional banks and fintechs reach a higher value of EPS.

Finally, the operational risk variables also have a consistent result in both types of banks. Similar to China, ORP and C/I have significant negative influences on EPS for Australian traditional banks. Thus, Australian traditional banks should be concerned with their operational efficiency and reduce issues of operational risks to achieve better EPS values. For fintechs, ORP and C/I have negative influences on EPS, and only ORP is significant at the 5% level. Moreover, a 1% increase in OPR will lead to a 0.1495% decrease in fintechs' EPS which is higher than the influence of C/I (e.g., 0.0065% decrease in EPS). Thus, the Australian fintechs should focus on particular issues of operational risks and reduce the costs of these to achieve better EPS values. Besides the similarities, one main difference is that risk variables show a higher influence level for traditional banks than fintechs with higher estimates. With respect to ROA and ROE performance, risk variables show higher impacts on fintechs than traditional banks with higher estimates. This indicates that traditional banks in Australia should pay more attention to risk management than the other two countries.

Similar to China and UK, besides interpreting variables, we looked at the R^2 for our EPS models. R^2(within) shows a 62% variation within one traditional banks over time and a 59% variation within one fintech over time. R^2(between) shows 71% variation between traditional banks and 68% variation between fintechs. R^2(overall) shows 56% for traditional banks and 33% for fintechs. We could find out that traditional banks have higher R^2s, which indicate higher variation was presented in traditional banks. Moreover, we could see that the R^2 for Australian traditional banks are all higher than fintechs which is opposite in China and the UK. This suggests Australian traditional banks have higher variation and they need to concern more about risk management as more differences exists between individuals over time.

In general, the estimates from our panel data regression models of traditional banks and fintechs in Australia provided similar results as showed in the other two countries. Firstly, all credit risk variables showed a negative influence on bank performance. This suggests that reducing credit risks could help both types of banks increase their performance. The difference is also visible for credit risk. Although all credit risk variables show a negative impact on the three countries' different bank performance, a different level of impact is indicated. Similar to the UK and Chinese banks, for ROA and ROE, credit risk has higher impacts on fintechs. However, it showed a higher impact on traditional banks than fintechs for EPS. This result shows (1) the importance of credit risk management in bank operations for both types of banks; and (2) the increasing trend of credit risk in traditional banks in Australia that cause concern with the market investment.

Secondly, LCR, CR and T1 showed a positive influence on bank performance. Thus, both types of banks should follow legal requirements to increase their liquidity and capital holding levels, which could help them reach a better level of performance. Thirdly, D/A and D/E showed a negative influence on bank performance. Thus, controlling the debt level could also help both types of banks improve their performance. For operational risks, the relevant variables showed a negative influence on bank performance. This suggests that for both types of banks, reducing operational issues and costs could increase their performance. Finally, developing the bank's reputation could help both types of banks increase their performance.

Furthermore, besides differences in credit risk variables and compared with the other two countries, ln(asset) has a positive impact on ROA, ROE and EPS for traditional banks, which suggests increasing bank size will help Australian traditional banks develop their performance. However, for Chinese traditional banks, ln(asset) have a negative impact on ROA, ROE and EPS, which suggests reducing useless or safety amount of assets will help Chinese traditional banks develop their performance. The possible reason for this is that traditional Banks in Australia are relatively small compared with those in China and have some room for development.

Therefore, for both traditional banks and fintechs, similar to the other two countries, a better reputation, healthy liquidity conditions, efficient credit risk management, lower debt and cost levels and alertness to market movements could provide better performance in both returns and on the stock market.

4.4.7 GMM estimates for Australia

Following section 4.2.7 and 4.3.7, this section will provide GMM to check if our results from the random-effects model are robust for Australian banks. Similar to China and UK, even though we called GMM a robustness checks for random-effects models, the results from GMM are as important as we got from random-effects. We will use and compare both approaches' results (Random-effects and GMM) to build our discussion and conclusions. Tables 4.40 to 4.42 GMM estimates for the impacts of risks on the bank performance (ROA, ROE and EPS, respectively) in Australia.

	Estimations	
	Traditional banks	Fintechs
Intercept	0.1972	-0.962
One period lag of ROA	0.0590	0.0482
Non-performing loan ratio	-0.3529*	-5.4985**
Net Charge-off rate	-0.2307	-10.9340*
Total loan loss ratio	-0.4400**	-7.4496*
Value at risk	-0.0001*	-0.0053
Liquidity coverage ratio	0.0014**	0.0108*
Current ratio	0.1481	0.0069
Tier 1 capital ratio	0.0648*	0.9913***
Debt-to Asset ratio	-0.0167**	-0.7458***
Debt-to-Equity ratio	-0.0004*	-0.0120***
Brand value change %	0.0045**	0.1050***
Operational risk %	-0.1495*	-0.1791
Ln(Asset)	-0.0002***	0.0458*
Cost-to-Income ratio	-0.0147	-0.0436**
F-test	459.2***	610.9***
Sargan Test (p-value > χ^2)	29.7 (0.429)	28.8(0.151)
AR(1)	z = -3.76 p-value = 0.00	z = -2.83 p-value = 0.00
AR(2)	z = -0.15 p-value = 0.88	z = -0.96 p-value = 0.34
No. of Obs.	95	82

Table 4.40 GMM estimation results (ROA, Australia)

Notes: *, **, ***represent significant at 10%, 5% and 1% respectively.

Sargan test is the test for over-identifying restrictions in GMM dynamic model estimation.

AR(1) and AR(2) are Arellano-Bond test that average autocovariance in residuals of order 1 and 2 is 0 (H_0: no autocorrelation).

Firstly, ROA was selected as the dependent variable to establish two GMM estimates based on bank type. Similar to China and UK, the F-statistics show the significance of the variables. The Sargan test shows that there is no evidence of over-identifying restrictions, and the Arellano-Bond test shows the consistency of our estimates for the independent variables.

For the Australian traditional banks, firstly, the significant coefficient of the lagged ROA confirms the dynamic character of the model specification. δ takes a value of 0.059, which suggests that the performance of the Australian traditional banks seems to persist. This implies that the Australian traditional banks have a nearly perfect competitive structure. This shows the higher competitiveness of the Australian traditional banks than the Chinese and UK traditional banks.

Turning to the other independent variables, similar results are presented as shown in our random-effects panel data regression models. Firstly, the credit risk variables have negative impacts. This suggests that higher credit risks lead to poor performance. In details, NPL and LoanR also significantly negatively impact the ROA at 10% and 5% significance level. With regards to coefficient values, a 1% increase of the NPL will lead to a 0.35291% decrease of the ROA, where NCO and LoanR could lead to a 0.2307% and a 0.44% decrease, representatively. Similar to random-effects models, LoanR shows its importance in credit risk management in both significance level and coefficient value. Thus, this suggests that managers should pay more attention to LoanR during credit risk management. Moreover, the values of the estimates are larger than were showed for Chinese and UK traditional banks. This suggests that the Australian traditional banks should be more concerned with these credit risk variables.

With regards to market risk, VaR has a significant negative impact on ROA at the 10% significance level. This suggests that higher market risk could decrease the ROA performance of Australian traditional banks. The result is also similar to the results from random-effects estimates, which suggest Australian traditional banks should reduce or keep alert to the market risks. Next, with regards to the liquidity, capital and debt level variables, consistent results are shown compared with our random-effects panel data regression models. The positive relationship between liquidity and capital holding level and bank performance and the debt level variables is negatively related to bank performance. LCR, CR and T1 all show positive impacts on ROA, where LCR and T1 are significant at the 5% and 10% level. With regards to coefficient values, a 1% increase in LCR will lead to a 0.0014% increase in ROA, where CR will lead to a 0.1481% increase and T1 will lead to a 0.0648% increase. The results indicate that increasing the liquidity and capital holding level could increase their performance. For debt level variables, both D/A and D/E negatively impact to ROA at the 5% and 10%

significance level. With regards to coefficient values, a 1% increase in D/A will lead to a 0.0167% decrease in ROA, where D/E will lead to a 0.0004% decrease. Similar to the results from random-effects, the GMM results suggest that a lower debt level could help banks to receive better performance. Managers should consider more on D/A with its higher significance level and coefficient value.

With regards to the operational risk variables, similar to our panel data regression models, both variables negatively affect ROA. ORP shows a higher significant impact on Australian traditional banks at the 10% significance level. Based on the coefficient values, a 1% increase of ORP or C/I will lead to a 0.1495% or 0.0147% decrease in ROA. A higher significance level and coefficient value for the ORP suggesting that Australian traditional banks need to concern more about their particular operational risks. In addition, a similar result is shown in the reputational risk variable. BVC shows a significant positive impact on ROA at the 5% significance level, where a 1% increase in BVC will lead to a 0.0045% increase in their ROA. This means that increasing reputation could help banks to increase ROA performance. Finally, with regards to bank size, ln(asset) significantly negative impacts on ROA at the 1% significance level. A 1% increase in ln(asset) will lead to a 0.0002% decrease in ROA. This result is not consistent with the results obtained from our random-effects models. As we already proved there is no endogeneity problem in our dataset, and the difference between the estimate is small. We could retain our suggestion, Australian traditional banks could keep their bank size to have a better performance.

For Australian fintechs, The F-statistics show the significance of the variables. The Sargan test shows there is no evidence of over-identifying restrictions. The AR tests show that the estimates of independent variables are consistent. With regard to lagged dependent variables, although it is not significant, the coefficient of the lagged ROA shows the dynamic character of the model specification. δ takes a value of approximately 0.0483, which suggests that the performance of the UK fintechs seems to persist to a perfectly competitive market structure in ROA. However, it is still lower than value showed in Chinese fintechs. This shows the higher competitiveness of

Chinese fintechs than Australian fintechs.

Estimates for the independent variables show results for ROA consistent with our random-effects panel data regression models. Firstly, all credit risk variables have negative impacts and the coefficient values of these variables are larger than were obtained for traditional banks. This confirms that credit risk hurts bank performance as in traditional banks, but that fintechs should be more concerned with these credit risk variables, as these variables have higher coefficient values and significance levels. Moreover, all three of them show their significance impact to fintechs' ROA. In these thee variables, NCO shows highest coefficient value, a 1% increase in NCO will lead to a 10.934% decrease in ROA. Thus, mangers should concern NCO more based on their coefficient values. With regards to market risks, result is consistent with random-effects. VaR shows a negative relationship with fintechs' ROA. A 1% increase in VaR will lead to a 0.0053% decrease in Australian fintechs' ROA.

With regards to the capital and liquidity risk variables, similar results are presented compared with results from random-effects models. Fintechs with a higher level of capital and liquidity holdings level and meet legal requirements for these variables could obtain better performance. In more detail, all three capital and liquidity variables positively impact the ROA. LCR and T1 have a 10% and 1% significantly impact, respectively. Based on coefficient values, a 1% increase in LCR will lead to a 0.0108% positive change of ROA, where CR shows 0.0069% and T1 shows 0.9913% positive changes to ROA. With regards to debt variables, the results show that both D/A and D/E have significant negative impact on Australian fintechs' ROA at the 1% level. A 1% increase in D/A or D/E will lead to a 0.7458% or 0.012% decrease in ROA. This result is consistent with our random-effects panel data regression models. Moreover, the results also present similar results on ROA compared with traditional banks' results. This suggests that a lower debt level could help Australian fintechs to achieve better performance. Thus, prioritising these variables in risk management based on their estimated values and significance could help managers achieve better efficiency and performance. For Australian fintechs, managers should concern more about T1 and D/A based on their higher significance level and coefficient values.

With regards to operational risk variables, both variables also show negative impact on ROA, where C/I is significant at the 5% level. A 1% change in ORP will lead to a 0.1791% decrease and C/I will lead to a 0.0436% decrease in fintechs' ROA. Similar to GMM estimates shown in fintechs for the other two countries, together with control over particular operational risks, Australian fintechs need to control their overall costs and increase their operational efficiency to obtain better performance. With regards to reputational risk variables, consistent results are shown compared with random-effects estimates for Australian fintechs and GMM estimates for Australain traditional banks. BVC also shows a significant positive impact on ROA at the 1% significance level, where a 1% increase in BVC will lead to a 0.105% increase in ROA. Thus, with is higher coefficient value, manager needs to keep fintech's brand value healthy, as increased reputation could help fintechs achieve better performance. Finally, similar to the random-effects estimates for ROA, there is evidence of a positive relationship between size and ROA performance. At the 10% of significance level, a 1% increase of fintechs' ln(asset) will lead to a 0.0458% increase of fintechs' ROA, which suggests that increasing size tends to better performance.

	Estimations	
	Traditional banks	Fintechs
Intercept	-0.2395	-2.3373
One period lag of ROE	0.1279*	0.2415***
Non-performing loan ratio	-0.2005**	-2.2513*
Net Charge-off rate	-0.3415	-14.2171*
Total loan loss ratio	-0.2746*	-7.8635**
Value at risk	-0.0004*	-0.0181*
Liquidity coverage ratio	0.0063	0.0836*
Current ratio	0.2053**	0.0034
Tier 1 capital ratio	0.0897*	0.2036*
Debt-to Asset ratio	-0.6153*	-0.0743
Debt-to-Equity ratio	-0.0211**	-0.0156*
Brand value change %	0.0117*	0.0861*
Operational risk %	-0.1273*	-0.1028**
Ln(Asset)	0.0204**	0.0128**
Cost-to-Income ratio	-0.2746	-0.1452*
F-test	412.4***	369.1***
Sargan Test (p-value > χ^2)	22.5 (0.799)	22.0(0.460)
AR(1)	z = -3.1 p-value = 0.00	z = -3.39 p-value = 0.00
AR(2)	z = -0.2 p-value = 0.84	z = -0.52 p-value = 0.60
No. of Obs.	95	82

Table 4.41 GMM estimation results (ROE, Australia)

Notes: *, **, ***represent significant at 10%, 5% and 1% respectively.

Sargan test is the test for over-identifying restrictions in GMM dynamic model estimation.

AR(1) and AR(2) are Arellano-Bond test that average autocovariance in residuals of order 1 and 2 is 0 (H_0: no autocorrelation).

Besides ROA, GMM estimates for ROE also show consistent results compared with random-effects panel data regression estimations. For traditional banks, similar to GMM for traditional banks in ROA, the F-statistics show the significance of the variables. The Sargan test shows there is no evidence of over-identifying restrictions. The AR tests show that the estimates of independent variables are consistent. For the lagged dependent variable, the significant coefficient of the lagged ROE confirms the dynamic character of the model specification. δ takes a value of 0.1279 when performance is measured by ROE. The result suggests that the performance of the UK's traditional banks seems to persist. This implies that the Australian traditional banks have a relatively competitive structure. This shows the higher competitiveness of the Australian traditional banks than the Chinese traditional banks, but lower competitiveness than the UK traditional banks.

Turning to the other independent variables, the results here for the dependent variables are consistent with our random-effect panel data regression models. Firstly, credit risk variables have negative impacts. This suggests that higher credit risks lead to poor ROE for Australian traditional banks. In details, NPL and LoanR significantly negatively impact the ROE at the 5% and 10% level. In these credit risk variables, the NCO has the largest coefficient number. A 1% increase of the NCO will lead to 0.3415% decrease of the ROE where NPL and LoanR could lead to 0.2005% and 0.2746%, representatively. Moreover, LoanR shows its importance in credit risk management based on the relatively high significance level and relatively highe coefficient value. With regards to market risk variables, VaR has a significant negative impact on ROE at the 10% significance level. The results are consistent with random-effects estimates. Australian traditional banks should keep VaR at a reasonable level and reduce the risk if possible, to achieve better performance.

Regarding the capital and liquidity risk variables, consistent results also show in GMM compared with random-effects. CR and T1 have significant positive impacts on ROE with the 5% and 10% significance level, where a 1% increase in LCR will lead to a 0.0063% increase in ROE. For CR and T1, a 1% increase in CR or T1 will lead to a 0.2053% or 0.0897% increase in traditional banks' ROE. Even though LCR do not appear significant in the ROE model, with its positive influence, managers should still keep LCR pass the legal requirement and at a healthy level. Moreover, the results show the importance of CR for traditional banks based on its high significance level and coefficient value. Thus, managers should follow the regulation requirements (e.g. Basel Accords) and increasing the capital holding level could help banks increase their performance. We further notice that the debt level variables are significant negatively related to bank performance at the 10% and 5% level. In more detail, a 1% decrease in D/A will lead to a 0.6153% increase in ROE where D/E shows a 0.0211% increase.

Similar to the results from random-effects, the GMM results suggest that a lower debt level could help banks receive better performance. Managers should consider more on D/A with its significance level and higher coefficient value.

With regards to operational risk variables, GMM also provides results consistent with our random-effects panel data regression models. Both variables affect ROE negatively, where ORP is significant at the 10% level. Based on the coefficient values, a 1% increase of ORP or C/I will lead to 0.1273% or 0.2746% decreases in ROE. Similar to the random-effects for ROE in traditional banks, managers in UK traditional banks should be concerned more with particular operational risks. For reputational risk variables, BVC shows a significant and positive impact on ROE at the 10% significance, where a 1% increase in BVC will lead to a 0.0117% increase in their ROE. This suggests that increasing reputation could help banks increase ROE performance. Finally, the coefficient for bank size significant positively impacts bank performance at the 5% significance level for ROE. This result is consistent with random-effects.

For Australian fintechs, The F-statistics show the significance of the variables. The Sargan test shows there is no evidence of over-identifying restrictions. The AR tests show that the estimates of independent variables are consistent. With regard to lagged dependent variables, the coefficient of the lagged ROE shows the dynamic character of the model specification. δ takes a value of approximately 0.2415, which suggests that the performance of Australian fintechs seems to a relatively competitive market structure in ROE. This shows a similar competitiveness of the Australian traditional banks with the Chinese traditional banks, but lower competitiveness than the UK traditional banks.

Estimates for the independent variables show results for ROE consistent with our random-effects panel data regression models. Firstly, all credit risk variables have negative impacts and the coefficient values of these variables are larger than were obtained for traditional banks. Moreover, all three variables (NPL, NCO and LoanR) significantly negatively impact the ROE at 10%, 10% and 5% significance level. For coefficient values, a 1% increase in NPL will lead to a 2.2513% decrease in ROE, NCO shows 14.2171% and LoanR shows 7.8635%. We could see that the coefficient values are larger than they showed in traditional banks like random-effects models. This confirms that credit risk hurts bank performance as in traditional banks, but that fintechs should be more concerned with these credit risk variables. Managers should focus more on NCO with its largest coefficient value, as all three variables show significant to ROE performacne. With regards to market risks, VaR shows a significant negative relationship with bank performance for ROE, where a 1% increase in VaR will lead to a 0.0026% decrease in ROE. However, the results from random-effects estimates show that VaR has a positive influence on ROE. As we tested, there is no endogeneity problem exist in our dataset, and the VaR is significant in GMM but not in random-effects. The result show here suggests that Australian fintechs should be concerned more with market risks. Moreover, as the results for the other two dependent variables are consistent, Australian fintechs should keep VaR at a reasonable level and reduce the risk if possible, to achieve better performance.

With regards to the capital and liquidity risk variables, similar results are presented compared with results from random-effects models. Fintechs which have a higher level of capital and liquidity holdings level and meet legal requirements for these variables could obtain better performance. In more detail, all of them positively impact on ROE, LCR and T1 show their positive impact at 10% significance level. Based on coefficient values, a 1% increase in LCR will lead to a 0.0836% positive impact on ROE, where CR shows a 0.0034% and T1 shows a 0.2036% positive impact on ROE. With regards to debt variables, the results show that both D/A and D/E have negative impacts, where D/E is significant at the 10% significance level on ROE. This result is consistent with our random-effects panel data regression models and traditional banks' results, which also presents the same results. With the coefficient values, a 1% increase in D/A will lead to a 0.0743% decrease in ROE, and a 1% increase in D/E will lead to a 0.0156% decrease in ROE. Thus, the importance of D/A is seen, which is proved by its higher coefficient value and significance level. This suggests that managers should consider more on D/A when managing risks.

With regards to operational risk variables, both variables also show significantly negative impacts on ROE, where the ORP shows a 5% significance level and C/I shows a 10% significance level. With regards to coefficient values, a 1% increase in ORP will lead to a 0.1028% negative change and C/I shows a 0.1452% negative impact. Similar to GMM estimates shown in fintechs' ROA, together with control over particular operational risks, UK fintechs also need to control their overall costs and increase their operational efficiency to obtain better performance. With regards to reputational risk variables, consistent results are shown compared with random-effects estimates, BVC also shows a significant positive impact on ROE at the 10% significance level, which suggests that increased reputation could help fintechs achieve better performance.

Finally, similar to the random-effects estimates for ROE, there is evidence of a positive relationship between size and ROE performance. At the 5% significance level, a 1% increase of fintechs' ln(asset) will lead to a 0.0128% increase of fintechs' ROE, which suggests that increasing size tends to result in better performance.

	Estimations	
	Traditional banks	Fintechs
Intercept	-0.9169	0.1010
One period lag of EPS	0.6175**	0.0585
Non-performing loan ratio	-2.1974**	-3.1224***
Net Charge-off rate	-2.779	-5.3974***
Total loan loss ratio	-0.9068*	-4.3349***
Value at risk	-0.0051*	-0.0052**
Liquidity coverage ratio	0.1119*	0.0035*
Current ratio	0.1459*	0.0014
Tier 1 capital ratio	0.9032*	0.1082*
Debt-to Asset ratio	-0.6208**	-0.0757***
Debt-to-Equity ratio	-0.2171	-0.0004*
Brand value change %	0.1253*	0.0098*
Operational risk %	-0.1585*	-0.2754***
Ln(Asset)	0.0479**	0.0003*
Cost-to-Income ratio	-0.1163*	-0.0217***
F-test	1245.7***	277.8***
Sargan Test (p-value > χ^2)	35.9(0.176)	15.3(0.849)
AR(1)	z = -4.59 p-value = 0.00	z =-3.17 p-value = 0.00
AR(2)	z = -0.69 p-value = 0.50	z = -0.45 p-value = 0.66
No. of Obs.	81	72

Table 4.42 GMM estimation results (EPS, Australia)

Notes: *, **, ***represent significant at 10%, 5% and 1% respectively.

Sargan test is the test for over-identifying restrictions in GMM dynamic model estimation.

AR(1) and AR(2) are Arellano-Bond test that average autocovariance in residuals of order 1 and 2 is 0 (H_0: no autocorrelation).

Finally, we are interested in observing whether the stock market's bank performance depends on managing different types of risks. The GMM estimates are applied to show coefficients and provide these results with EPS in Table 4.42.

For traditional banks, similar to GMM for traditional banks in ROA and ROE, the F-statistics show the significance of the variables, the Sargan test shows there is no evidence of over-identifying restrictions, and the AR tests show the estimates of independent variables are consistent. With regard to lagged dependent variables, the coefficient of the lagged EPS shows the dynamic character of the model specification.

δ takes a value of 0.6175 when performance is measured by EPS. This result also suggests that Australian traditional banks' performance seems to persist in a moderate competitive market structure in EPS.

Turning to the other independent variables, the results here for the dependent variables are consistent with our random-effect panel data regression models. Firstly, credit risk variables have negative impacts on EPS. This suggests that higher credit risks lead to poor EPS for UK traditional banks. In details, NPL and LoanR significantly negatively impact the EPS at the 5% and 10% level, respectively. In these credit risk variables, the NCO has the largest coefficient number, a 1% increase of the NCO will lead to a 2.779% decrease of the EPS where NPL and LoanR could lead to 2.1974% and 0.9068% decrease, representatively. Similar to random-effects models, NPL shows its importance in credit risk management based on the highest significance level together with its relatively high coefficient value. With regards to market risk variables, VaR has a significant negative impact on EPS at the 5% significance level, which is similar to the results from random-effects estimates. Thus, in order to increase the bank's EPS, managers should control the VaR relatively low.

Regarding the capital and liquidity risk variables, consistent results also show in GMM compared with random-effects that all three variables positively significant influence the bank performance at the 10% significance level. As all variables is significant, managers should consider more on coefficient. Based on coefficient values, T1 shows the highest where a 1% increase T1 will lead to a 0.9032% increase of EPS. This suggests that the importance of T1 during capital risk management. Managers should follow the regulation requirements (e.g. Basel Accords) and increasing the capital holding level could help banks increase their performance. We further notice that the debt level variables are negative related to EPS, where D/A is significant for EPS at the 5% level. In addition, D/A also shows higher coefficient value than D/E, where a 1% increase in D/A will lead to a 0.6208% decrease in EPS. Similar to the results from random-effects, the GMM results suggest that a lower debt level could help banks to receive better performance.

With regards to operational risk variables, GMM also provides results consistent with our random-effects panel data regression models. Both ORP and C/I affect EPS significantly and negatively at the 10% level. Based on the coefficient values, a 1% decrease of ORP or C/I will lead to a 0.1585% or 01163% increase in EPS. As both variables show their significance, managers in Australian traditional banks should control their operational risks during the business, especially in the stock market. For reputational risk variables, BVC shows a positive impact on EPS at the 10% significance level, where a 1% increase in BVC will lead to a 0.1253% increase in their EPS. The result suggests an increasing reputation could help bank increase EPS performance. Finally, the bank size significantly positive impacts bank performance at the 5% significant level for EPS. With a 1% increase in ln(asset), the UK traditional banks' EPS will increase 0.0479%. The result is consistent and managers should improve their bank size to increase EPS performance.

For Chinese fintechs, the F-statistics show the significance of the variables. The Sargan test shows there is no evidence of over-identifying restrictions. The AR tests show that the estimates of independent variables are consistent. For the lagged dependent variable, the significant coefficient of the lagged EPS confirms the dynamic character of the model specification. δ takes a value of approximately 0.0585, which suggests that the performance of the Australian fintechs seems to persist to a perfectly competitive extent in EPS.

Estimates for the independent variables show results for EPS consistent with our random-effects panel data regression models. Firstly, all credit risk variables have negative impacts and the coefficient values of these variables are relatively larger than were obtained for traditional banks. This confirms that credit risk hurts bank performance as in traditional banks, but that fintechs should be more concerned with these credit risk variables. As all three variables are significant at the 1% level, managers should concern more on NCO because of its highest coefficient value. With regards to market risks, VaR shows a significantly negative relationship with EPS at the 5% level, where a 1% decrease in VaR will lead to a 0.0052% increase in EPS. In addition, fintechs are more related to other markets and have a smaller market scale than UK traditional banks. Thus, they should take more care about market risks with their relatively weak market position in the financial system, especially in the stock market.

With regards to the capital and liquidity risk variables, similar results are presented compared with results from random-effects models. Fintechs which have a higher level of capital and liquidity holdings level and meet legal requirements for these variables could obtain better performance. All of them positively impact the EPS, where LCR and T1 show their significance at the 10% significance level. Based on coefficient values, T1 shows the highest value, where a 1% increase in T1 will lead to a 0.5563% positive change to EPS. With regards to debt variables, the results show that both D/A and D/E have significant negative impacts on EPS at the 1% and 10% significance level. This result is consistent with our random-effects panel data regression models. With the coefficient values, D/A has higher coefficient value than D/E. A 1% increase in D/A will lead to a 0.0757% decrease in EPS. Thus, the importance of D/A is seen, which is proved by its higher significance level and coefficient value. This suggests that managers should consider more on D/A when managing debt level risks.

With regards to operational risk variables, both variables also show significantly negative impacts on EPS at the 1% level, where a 1% increase in ORP will lead to a 0.2754% decrease and C/I shows a 0.0217% negative impact. Similar to GMM estimates shown in fintechs' ROA and ROE, together with control over particular operational risks, managers also need to control their overall costs and increase their operational efficiency to obtain better performance. With regards to reputational risk variables, consistent results are shown compared with random-effects estimates and GMM estimates for both types of banks. BVC also shows a significant positive impact on EPS at the 10% significance level which suggests that every 1% increase in BVC could help fintechs achieve a 0.0098% increase in EPS performance. Finally, similar to the random-effects estimates for EPS, there is evidence of a positive relationship between size and EPS performance. At the 10% of significance level, a 1% increase of fintechs' ln(asset) will lead to a 0.003% increase of fintechs' EPS, which suggests that increasing size tends to result in better performance.

Similar to China and the UK, the F-statistics show the significance of the variables, the Sargan test shows there is no evidence of over-identifying restrictions, and the Arellano-Bond test shows the consistency of the estimates for the independent variables. For the Australian traditional banks, firstly, the significant coefficient of the lagged performance variables (ROE and EPS) confirms the dynamic character of the model specification. This suggests that the performance of the Australian traditional banks seems to persist and implies that Australian traditional banks have a relatively competitive structure. This result indicates that the UK traditional banking industry has the most competitive structure of all three countries.

Turning to the other independent variables, similar results are presented, as shown in Chinese and UK traditional banks. Firstly, credit risk variables have negative impacts. This suggests that higher credit risks lead to poor performance which is also demonstrated through our random-effects panel data regression models. With regards to market risk, VaR has a significant negative impact on all three bank performance variables. This suggests that higher market risk could decrease the performance of Australian traditional banks, which suggests that Australian traditional banks should reduce their market risk to achieve better performance. With its high significance, managers should be focused more on VaR when managing bank operations.

With regards to liquidity, capital and debt level variables, consistent results are shown compared with our random-effects panel data regression models. There is a positive relationship between liquidity and capital holding level and bank performance while the debt level variables are negatively related to bank performance. This suggests that in order to obtain better performance, Australian traditional banks should increase their liquidity and capital holding levels, and reduce their debt level. Based on their different significant levels, managers could prioritise them during management to achieve higher efficiency. Moreover, consistent results are shown in operational risk variables and the reputational risk variable. In more detail, Australian traditional banks should be concerned more with particular operational risks, then with controlling their general costs of operation. Also, Australian traditional banks should increase their reputation, which could help them to increase bank performance. Finally, with regards to bank size, the coefficient of bank size is significant and negatively impacts on ROA, but positively impacts on ROE and EPS. This result is also not consistent with the results received from our panel data regression models for ROA. However, the difference between the estimates is small and results still consistent for the ROE and EPS. Our overall suggestion for Australian traditional banks is retained, and is to maintain assets at a similar level and find a balanced point to achieve better performance.

For Australian fintechs, firstly, the significant coefficient of the lagged performance variable (ROE) confirms the dynamic character of the model specification.This suggests that the performance of Australian fintechs seems to persist, and shows that they have a relatively competitive structure. Similar to traditional banks, the result suggests that the UK fintechs also have a more competitive structure than the other two countries.

Turning to the other independent variables, GMM estimations also provide consistent results. Firstly, similar to the Chinese and UK fintechs, all credit risk variables have negative impacts on bank performance. Moreover, the values of the estimates are larger than shown in traditional banks. This confirms that credit risk hurts bank performance, and fintechs should be concerned about these credit risk variables. A difference exists in EPS for the Australia dataset. With the random-effects panel data regression models, the impact level is much higher in traditional banks, but in the GMM estimates, the impact level is similar to fintechs. As they all have negative impacts on bank performance, this suggests that both types of Australian banks should pay more attention to credit risk than the other two countries. With regards to market risks, VaR shows consistent results with Australian traditional banks. VaR has a negative relationship with all three dependent variables. Moreover, as VaR is significant for ROE and EPS at the 10% and 5% level, Australian fintechs should monitor market changes and reduce VaR to achieve better performance.

With regards to the capital and liquidity risk variables, consistent results are seen. Thus, fintechs which have a higher level of liquidity and capital and meet the legal requirements in liquidity and capital holding level could achieve better performance. With regards to the debt level variables, both of them show a negative relationship to bank performance. This suggests that a lower debt level could help Australian fintechs to achieve better performance. Thus, with regards to this type of risk, managers should prioritise these risk variables to achieve better management efficiency. In addition, similar results were also obtained for the operational risk variables. Both ORP and C/I show their significant negative impact on ROE and EPS, and C/I is also significant for ROA at the 5% level. This shows the importance of operational risk management. Thus, Australian fintechs should control in particular their operational risks and overall costs, which could help them increase their operational efficiency and achieve better performance. Finally, both BVC and ln(asset) show a significant positive impact on bank performance. Thus, in order to have good performance, Australian fintechs should increase their reputation and size during operation.

In summary, the GMM estimations provided consistent results for traditional banks and fintechs in Australia as those shown in our panel data regression models. The robustness check reinforced our findings of the impact of risks on Australian bank performance.

4.4.8 Summary

In this section, we analysed 22 Australian banks and listed them as two types (11 traditional banks and 11 fintechs). Firstly, we applied figure comparisons between traditional banks and fintechs. Then, descriptive statistics, stationarity, multicollinearity, heteroscedasticity and endogeneity tests were presented and analysed. Finally, by using ROA, ROE and EPS as dependent variables, we employed panel data regression models to study the impact of different types of risks on the performance of both types of banks. Moreover, as we used random-effects estimates to build a generalised model for the dataset. We did not need to add time- or individual- influence factors in the analysis, as they already be analysed through R^2.

The overall conclusions were consistent with the Chinese and the UK analysis, which was that improving different bank risk management could help the Australian banks achieve more successful performance. However, Australian banks showed more potential for risk management failure. Thus, prioritising these risks should be more meaningful to help Australian banks achieve better future performance. For traditional banks, more attention should be paid to capital and liquidity risk. Secondly, they need to consider their credit risks and not let them grow through time. Next, traditional banks should be concerned with market risks and operational risks. Moreover, Australian traditional banks should keep their size and reputation at a safe level. Fintechs, on the other hand, need to be more concerned about their liquidity and capital risks, then pay attention to credit risks and operational risks at the same time. Thirdly, fintechs need to stay alert to market movement. Finally, they need to try to increase bank size and reputation if possible. Therefore, managers could know the influence level of different types of risks and variables by prioritising these risks. They could further provide a more efficient strategy when managing risks. In addition, managers could estimate their future performance through our models and set risk management targets. Moreover, through our models, managers could better understand their competitors, which could help them avoid some mistakes or improve some advantages through management.

At the same time, investors and shareholders in Australia could also benefit from our models. By finding the relevant variables from banks/fintechs official website or any legal ways, investors and shareholders can receive different results based on the bank type. This could help them know if a bank/fintech develops or which bank/fintech is better to invest in these days. Similarly, policymakers and governments in Australia could also benefit from our models. Instead of investing in banks/fintechs, they can find banks/fintechs perform better or worse than others which can help them keep their eyes on these banks/fintechs and support or shut down these banks/fintechs. Moreover, through our models, policymakers and governments can understand the general situation for different bank types, which can help them make more targeted regulatory requirements based on bank type. More discussion could be found in Chapter 6.

Differences and similarities were listed for Australian traditional banks and fintechs, as well as general similarities and difference between Australian banks, UK banks and Chinese banks. Based on the process in this section, the following section applies conclusions for this chapter.

4.5 Conclusion

This chapter presented our quantitative results and discussed risk management and its impacts on bank performance through panel data regression models. Findings are further reinforced through GMM estimates. The discussions centred on the risk characteristics that were developed in Chapter 2 on the basic ingredients and strategies required by traditional banks and fintechs to create smooth risk management and operations.

The findings in this research showed that different kinds of risks have different impact levels based on the type of bank and the country where the bank resides. The main contribution of this chapter is that it not only analysed traditional banks in random-effects and GMM estimates. It also applied these approaches to the new types of banks -i.e. challenger banks and fintechs - to obtain results and compare them with the results from traditional banks. The results suggest that, in general, traditional banks performed relatively stables during the investigated time period. However, the fintechs' performance was not as good as expected, and there was a room for fintechs to improve their performance and risk management. Moreover, the results were also influenced by the country where these banks mainly operate. In summary, all banks need to improve their risk management efficiency and prioritise risks based on their significance and estimated values which could help them to achieve better performance.

Moreover, during analysis, we found out that outliers existed in fintechs' dataset. Although outliers are a part of the performance of these fintechs, we should keep them in the analysis. In order to check the influence of these outliers, we rerun the random-effects and GMM estimates for Australian fintechs without outliers. The reason for the only rerun of the Australian dataset is that for Chinese and UK fintechs, there are not enough observations to test the EPS by deleting the outliers. Thus, we should give fintechs a longer time to join the share market, and then we will have enough data to analyse. The detailed analysis for Australian fintechs can be found in Appendix 3 and 4.

Based on the analysis in Appendix 3 and 4, we could find consistent results. For random-effects estimates, the results are consistent with all dependent variables (ROA, ROE and EPS) found in Section 4.5, except for the D/E influence on EPS. D/E shows a negative impact on the EPS in random-effects estimates without outliers. However, the change of influence of the D/E does not impact our suggestion as we found the negative impact of D/E on the EPS in GMM estimates within outliers. Our results provide further evidence of the importance of running random-effects and GMM estimates simultaneously to test the dataset. Thus, our suggestion is consistent: managers should control and reduce the debt level, which will improve the fintechs' performance in the risk management process. For GMM estimates, the results are consistent with all dependent variables (ROA, ROE and EPS) found in Section 4.5. Thus, based on our analysis for Australian fintechs without outliers, the overall conclusions are consistent with the analysis in Section 4.5. This suggests that outliers will influence the estimates when analysing the dataset, but the influence is limited, the overall conclusions will be consistent. Even without outliers, fintechs still need to improve the efficiency of their risk management to help them achieve successful performance. Furthermore, as outliers are part of the performance of these fintechs, we cannot simply remove them and then analyse the rest of the data.

CHAPTER FIVE

CASE STUDIES

5.1 Introduction

As mentioned in Chapter 3, Easterby-Smith et al. (2002) said that a mixed research method could provide more significant empirical results and support for the research question. Thus, in order to have more significant results and achieve the research aim, besides analysing panel data regression estimates and GMM estimates, case studies are applied in this research for all three countries (China, the UK and Australia). Similar to the quantitative method, the investigation period started in 2013, when the influence of the 2007-09 financial crisis was still silt, and governments had begun to publish new requirements for banks. Thus, it is essential to investigate how these banks managed their risks during operations. On the other hand, as technology develops, the fintechs began to establish and develop during the investigation period. It is also essential to investigate how these newly established fintechs managed risks. However, there are limitations when selecting fintech cases. For the failure cases, we cannot access their data to analyse. The main reason is that almost every fintech operates online. When it closes its business, the data vanishes from the internet. Thus, we could not access any data for closed fintechs. Moreover, fintechs that operate poorly could either delay or not publish their financial and risk performance. Therefore, in this research, we could only choose those fintechs that published annual or interim reports. Although there are limitations in selecting fintech cases, our selected cases can still help us to see how fintechs operate in risk management. We can also provide suggestions for fintechs' managers based on our findings on selected cases.

Therefore, following Docherty and Viort (2014), we selected six banks and listed them in Sections 5.2 to 5.7. These cases contain lessons on the themes of risk management in the bank and their supervision. In selecting the cases, we attempted to cover risk management development and performance. In general, we could say that banks with better risk management might claim better performance. Moreover, we chose these cases where there was a public information source about their risk management process. After analysing these cases individually, Section 5.8 provides a comparison between these cases. Finally, Section 5.9 concludes this chapter.

5.2 Industrial and Commercial Bank of China (ICBC)

ICBC is one of the world's largest traditional banks. It was founded in 1984, joined the share market in 2006, and became the most valuable bank in the world by 2008 (ICBC, 2014). Based on the global economic environment and internal competencies, the strategy of ICBC is divided into three parts. Firstly, risk management should be mainly considered during operations. Secondly, a stable and balanced condition in assets and liabilities need to be maintained during operations. Finally, management skills, information technology, business cooperation, and global involvements need to be kept innovating during operations (ICBC, 2015).

Development of ICBC

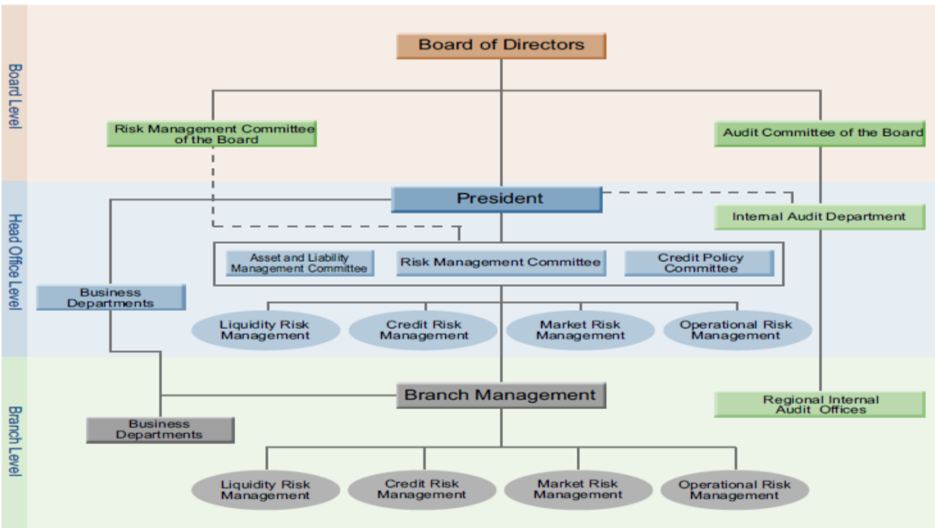
The main reason for the establishment of the ICBC was the Chinese economic reform in 1978. The Chinese government operated the ICBC from 1984 to 2005. Since China joined the WTO in 2001, the ICBC began a plan to join the share market. At the end of 2006, the ICBC joined both Shanghai and Hong Kong share market and became the second most valuable bank in market capitalisation in the world (ICBC, 2014).

ICBC published its first annual report in the year 2002. From 2002 to 2006, the annual reports just published information based on the Chinese regulations and the Basel Accords, such as general performance during the year, financial statements, and governance statements. In 2006, the annual report mainly focused on the event, which was that the ICBC joined both the Shanghai and Hong Kong share markets. In this study, we will mainly focus on risk management and financial statements. However, before the financial crisis, the ICBC annual reports did not have separate risk reports. It was only one part of the management reports. One possible reason for this could be that risk management was not seriously considered during the management process before the financial crisis.

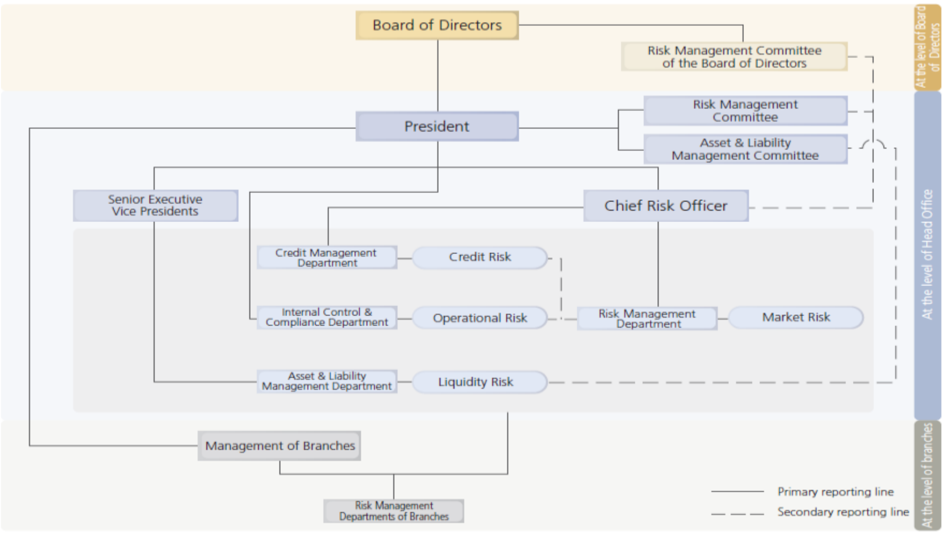
The consequences of the financial crisis led many banks and financial institutions to bankruptcy and influenced the global financial system, such as share markets falling globally, especially in Western countries. In China, the speed of development slowed, but there was an increasing trend. With the involvement of the Chinese government, as reflected in annual reports, ICBC began to pay more attention to risk management. For example, it established separate risk reports alongside its management reports. It also added more analysis of different types of risks, particularly in credit risk and liquidity risk.

Risk management development

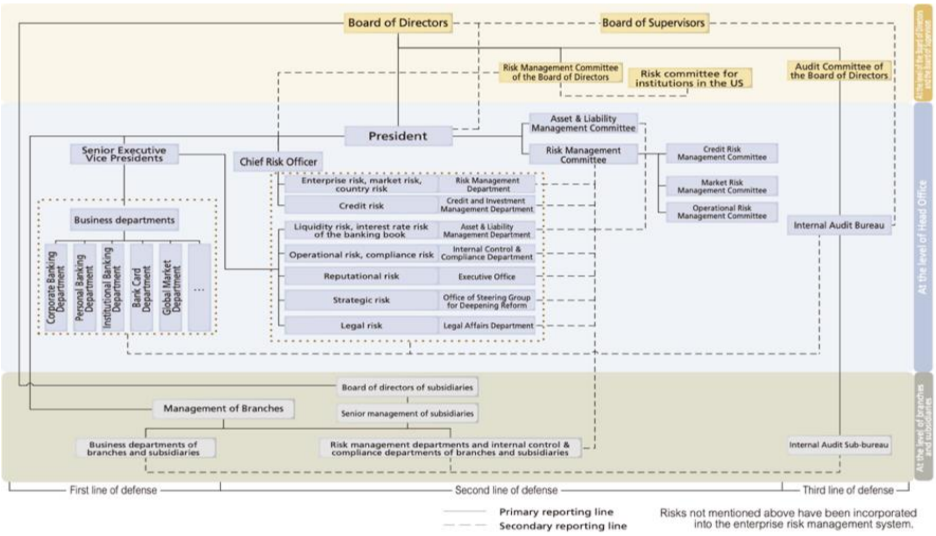
Before the financial crisis, the whole enterprise risk management system was straight forward and simple. Because of the financial crisis and the publishing of Basel II, ICBC strengthened innovations in its risk management system, which tried to optimise the bank's risk appetite indicators. Figure 5.1 shows the development of risk management systems for ICBC. In general, risk management in ICBC had four principles. The first is that it divided risk management responsibility. The second is of a centralised management role in monitoring risks. Thirdly, it divides the functions of front, middle and back offices. Finally, it provides a matrix-form risk report system for the bank. Also, with development, risk management became more detailed and comprehensive.



Risk management system in 2005



Risk management system in 2010

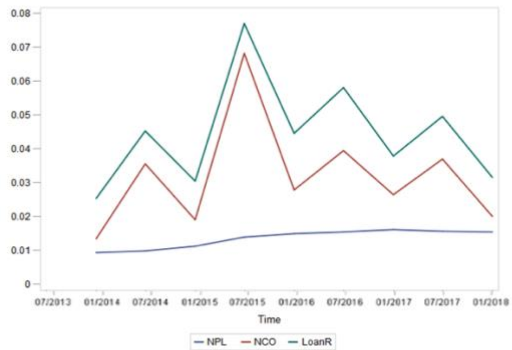


Risk management system in 2017

Figure 5.1 Risk management system development (ICBC)

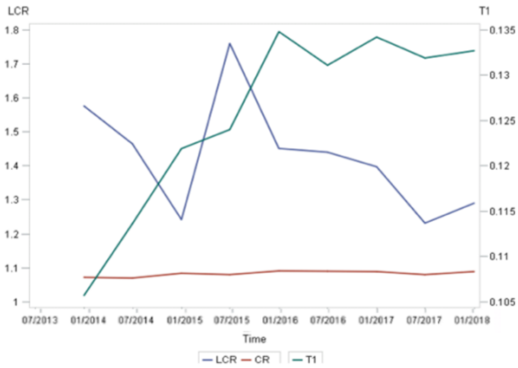
In more detail, with the risk variables we collected, the risk management performance for ICBC is shown in Figure 5.2. The credit risk management of ICBC provided a low level of credit risks. This suggests that the general credit risks for ICBC were held at a lower level. However, for NCO and total LoanR, it had an increasing trend before 2015 and decreasing after 2015. This shows that although the impact of the financial crisis was limited for Chinese traditional banks, it still increased the credit risk level. With efficient risk management and regulations, it then decreased. For market risk, as one of the Chinese traditional banks, market risk showed limited impact during its operation with relatively low VaR values.

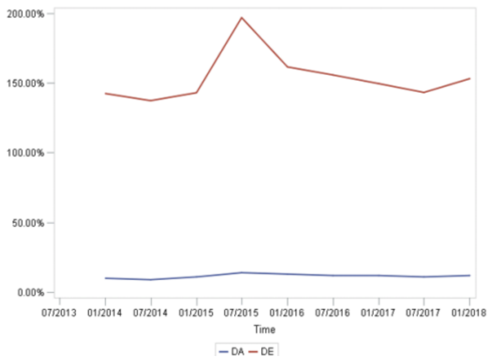
With regards to the capital and liquidity risks, these showed an increased capital level, a stable liquidity situation and a controllable debt level that suggests smooth liquidity and capital risk management of the ICBC. For the reputational risks, as the ICBC developed, in general, the bank increased its brand value. Finally, the operational risk variables showed increased efficiency of operation and a controllable and low level of operational risks.



Credit risk

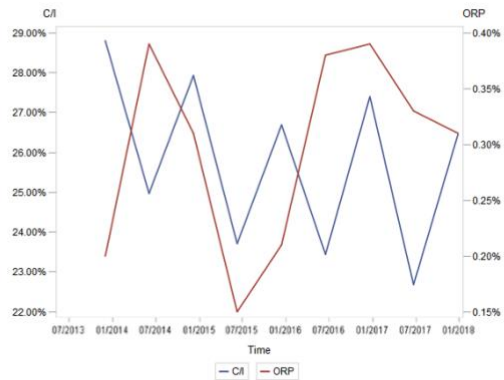
Market risk





Capital & Liquidity risks

Reputational risks



Operational risks

Figure 5.2 Risk performance of ICBC

Lessons

Although Chinese traditional banks, including ICBC, did not suffer a lot in the crisis, their development rate slowed down. At the same time, the Chinese government released a series of regulations to protect Chinese banks from the financial crisis with its further recessions. In 2009, ICBC began to follow a new regulation called 'Measures for capital adequacy ratio management of commercial Banks'. In 2012, it began to follow the developed regulation called 'Measures for the administration of capital and liquidity management in Chinese commercial banks'. Besides following the regulations, ICBC also improved its risk management in the management group, as well as its skills and models.

In summary, the annual reports of ICBC became more and more transparent and easy to understand and analyse. This reflects the ICBC's situation in each year and its development. In general, by following the government regulations, ICBC got though the recent financial crisis smoothly and became the world's most valuable bank. As an example of the Chinese traditional banks, it provided a relatively stable performance and had efficient risk management amongst the Chinese traditional banks.

5.3 YiRenDai (YRD)

Yirendai is one of the most famous fintechs in China. It was founded in 2012, joined the share market in 2015 and became the first fintech of China which joined the NYSE. YRD had a risk management system that mainly focused on credit management and fraud detection. YRD aimed to use the risk management system to operate more effectively in the market (YRD, 2016).

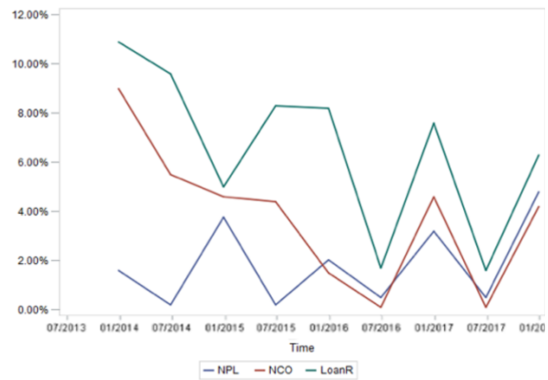
Development of YRD

Under the impact of the financial crisis, there was an explosion in financial technology. Together with the support of the Chinese government for fintechs, the YRD was established. Before 2015, as a newly established fintech company, it concentrated on public benefits and advertised itself to build better brand value in order to attract more customers and investors. In 2013, it received the 'Good Picture Winners' and 'Social Responsibility Award'. At the same time, with its development in its operations, it also received the 'Top ten fintechs brand in China' (YRD, 2018). After joining the share market, YRD developed rapidly, with a series of awards in China, and it became one of the most influential Chinese fintechs. YRD published its first annual report at the end of 2015 after it joined the share market. YRD published risks analysis in different parts of its annual reports in line with the traditional banks. As a newly established fintech, it presented fewer changes in its annual report during the investigated period.

Risk management development

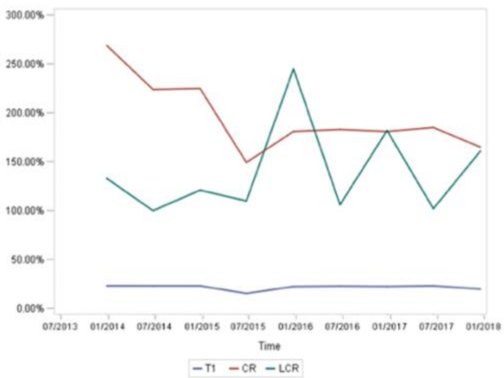
Risk management performance for YRD was shown in Figure 5.3. Credit risk management of YRD showed a relatively higher level of credit risks than ICBC, which was consistent with the results showed from our quantitative analysis. However, as these variables had a decreasing trend, this suggests that the general credit risks for YRD were under control. For market risk, even though YRD joined the NYSE, the main investments and operations of YRD were in China. As the small size of YRD, the general level of the VaR was small. With development, the VaR would near the level of ICBC. Also, because of its small size, even the low VaR may cause issues, so YRD, as well as other Chinese fintechs, need to be alert to market movements to maintain efficient operations.

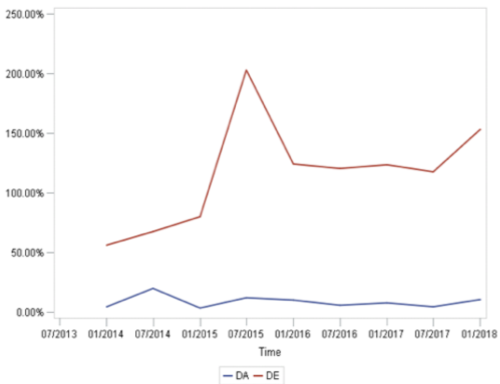
With regards to the capital and liquidity risks, YRD passed the Basel Accords requirements in liquidity coverage and tier one capital holdings. This suggests a relatively good position of YRD for preparing liquidity and capital to prevent bankruptcy. For the debt level variables, both variables had a low and stable portion which suggests a relatively good debt level. For the reputational risks, as YRD developed, it had an explosion in brand value at the beginning when it was established. As it operated for a longer time, the increase in brand value slowed to a small level. At last, with regards to the operational risk variables, these show increased efficiency of operations and improved control of the level of operational risks.



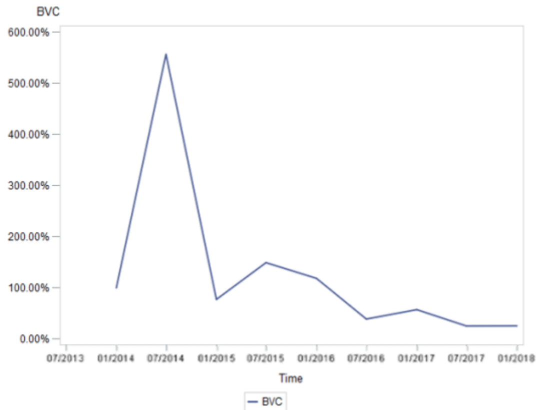
Credit risk

Market risk

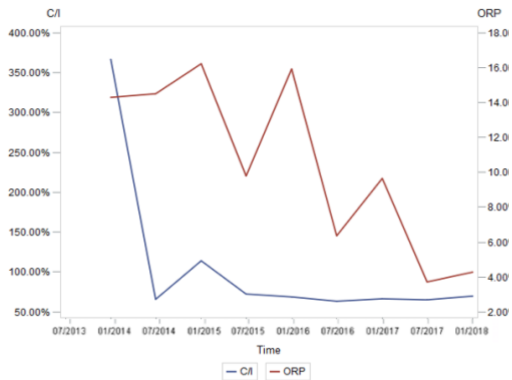




Capital & Liquidity risks



Reputational risks



Operational risks

Figure 5.3 Risk performance of YRD

Lessons

In summary, as an example of Chinese fintechs, YRD was relatively well developed in its performance and risk management during the investigated time period. With experiences from the traditional banks, the annual report of YRD started from a clear and easy format to understand and analyse. It reflected a good start point and its development during the years was also relatively good. In general, by following government regulations, YRD developed itself quite a lot and became one of the most famous Chinese fintechs, and good future performance could be expected.

5.4 HSBC

HSBC is one of the world's largest and most influential traditional banks. It was founded in 1836 and had an over 180-year history. At the end of 2017, its balance sheet was $2,522bn in size, its equity was $198bn, and it had 228,687 employees (HSBC, 2019).

Based on the global economic environment, a low-risk strategy is the primary strategy of HSBC during its operations. HSBC maintained a conservative and consistent approach to its risks throughout its history. The key elements include: keeping a stable balance in equity, keeping a worked risk profile strategic and financial planning process; and keeping operating smooth. With its vital risk appetite metrics, until 2018, capital and credit risks were two main risks faced by the HSBC groups (HSBC, 2019).

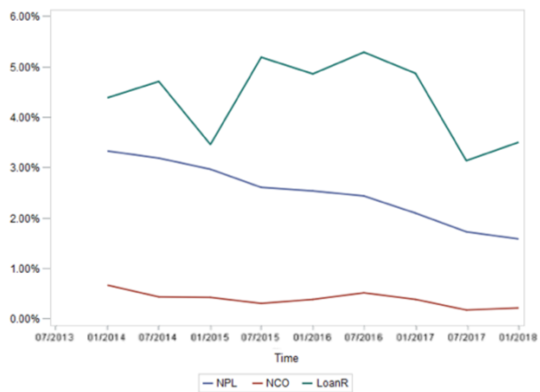
Impacts of the last financial crisis on HSBC

Because of the global operations of HSBC, the last financial crisis showed more impacts on HSBC than it showed on ICBC. For example, in February 2007, HSBC informed the market that its mortgage losses in the US were significantly worse than market assumptions. With this impact, its share price dropped to a low in March 2009, and after March 2009, it has been recovering. This shows that even an experienced institution could get the financial crisis wrong in the case of HSBC in its expansion into the US subprime problem. However, with its scale and diversification, this enabled HSBC to take the losses fine and stay solid. Since then, HSBC has kept tighter control and process reviews for its risks (Docherty & Viort, 2014; HSBC, 2010; HSBC, 2013).

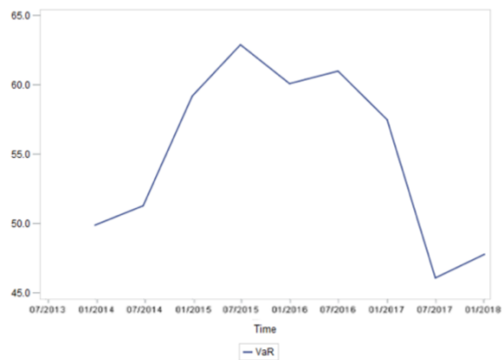
Risk management development

Risk management performance for HSBC is shown in Figure 5.4. With the impacts of the financial crisis, the credit risk management of HSBC provided relatively high starting points. Similar to the overall traditional bank performance in the UK, credit variables showed a decreasing trend. This suggests that HSBC increased its credit risk management efficiency. For market risk, there shows similar results for HSBC as it shows in the descriptive statistics. With the higher global connections of the UK and its higher currency value, the VaR of HSBC stayed at a higher level than that of ICBC.

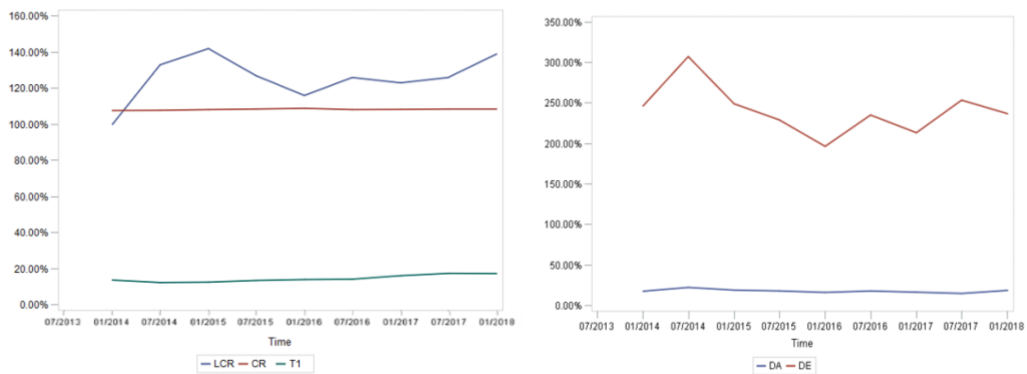
With regards to capital and liquidity risks, the liquidity and capital levels of HSBC showed a flat trend with its development. This suggests that HSBC kept its situation stable from the financial crisis in liquidity and capital level. With respect to reputational risks, with the influences of the financial crisis, the movement of the HSBC brand value wavered. In general, HSBC increased its brand value slightly, and its brand value remained healthy and unchanged. Finally, the ORP of HSBC was always controllable. However, the operational efficiency stayed at a relatively low level after the 2007-09 financial crisis. Moreover, with an increasing trend of C/I, the priority of operational risks became high. Managers should pay more attention to controlling their operational costs to achieve better operational efficiency.



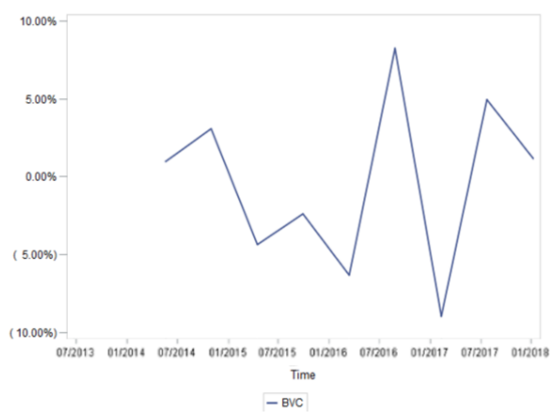
Credit risks



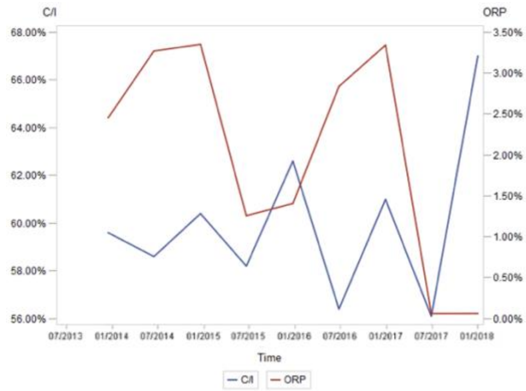
Market risk



Capital and liquidity risks



Reputational risk



Operational risk

Figure 5.4 Risk performance of HSBC

Lessons

HSBC suffered more than ICBC during the last financial crisis, but through a low-risk strategy and well-established operations systems, the performance of risk management was under control during the following years. In summary, risk management reports in annual reports of HSBC were already developed well with its long history, which made it easy to access risk reports to analyse. In general, HSBC applied consistent and diverse risk management, has stayed strong in recent years and is still one of the most important traditional banks in the world.

5.5 Atom Bank (Atom)

Atom was the first fintech that received a bank licence to be established in the UK. It was founded in 2014 and planned to join the share market with pre-IPO. In June 2015, Atom received its licence from the Prudential Regulation Authority (PRA) and the FCA before it launched in November 2015. With its development, the Atom team had grown to 350 people in 2019 (Atom, 2019).

Development of Atom

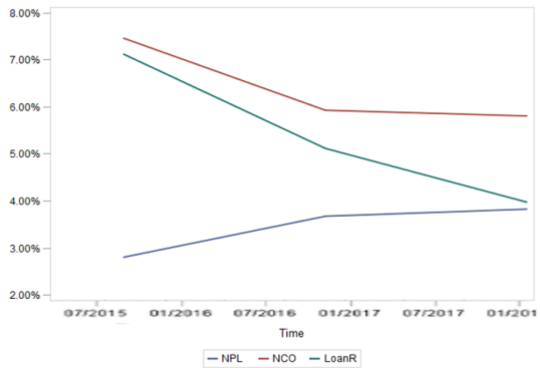
As mentioned above, Atom bank had a short history. After it received a bank licence and launched in 2015, in December 2016, it launched residential mortgages. In January 2017, it launched new products in its fixed saving business. By increasing its saving rates higher than all other banks, it attracted media attention and UK customers. In the same year, it was named one of the UK's top 25 start-ups, and in 2018, it was named in KPMG's Global 100 fintechs list with a ranking at nine, which is the highest-ranked business in the UK (Atom, 2019). With these benchmarks happening for Atom, it shows quite a lot of development for Atom.

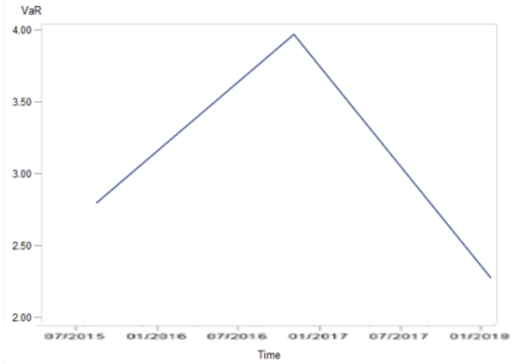
Risk management development

Besides developing, Atom also built a risk management framework to help improve efficiency in its operations. It listed several risks faced by Atom and applies risk management strategies. The performance of risk management is shown in Figure 5.5. In more detail, with respect to credit risks, the overall credit risk values are larger than HSBC. The results are similar to China, where fintechs (e.g., YRD) has higher credit risk values than traditional banks (e.g., ICBC). Moreover, the credit risks were all under control. This suggests that the credit risk management of Atom stayed at a relatively good level. For market risk, because of its small size and because it had not yet joined the share market, Atom had a low level of VaR. Moreover, because of the short time since its establishment, there was not a clear trend of the VaR. We should give more time for Atom to see how will it react to more market risks.

With regards to the capital and liquidity risks, Atom showed a developing trend with these variables. For example, LCR showed an increasing trend which indicates a good liquidity coverage level. This suggests that Atom has prepared more liquidity to deal with liquidity issues during operations. T1 stayed at a smooth level and passed the requirement of the Basel Accords. Moreover, the debt level variables showed a stable trend which indicates a controllable debt level for Atom.

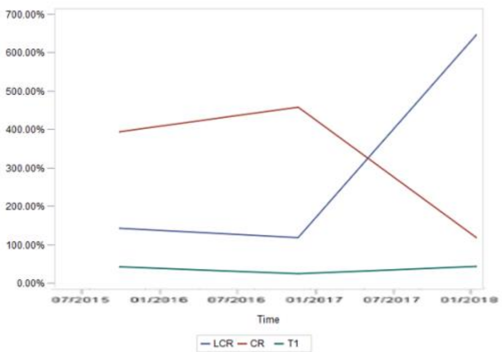
With regards to BVC, as noted in the Atom's development, the brand value of Atom increased a lot at this stage, which is confirmed in Figure 5.5. Finally, with regards to operational risks, these showed a v-sharp for both variables, which suggests that from the beginning of 2017, the costs and operational risks for Atom started to increase. However, as Atom had a short history, more time is needed to see its overall operational risk management performance.

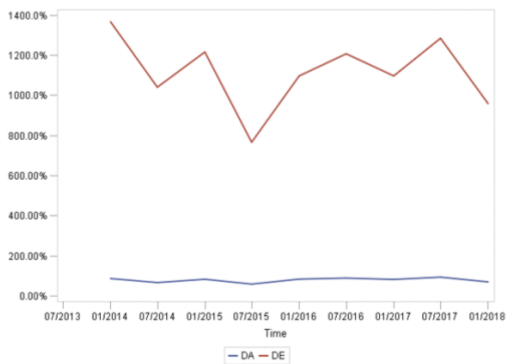




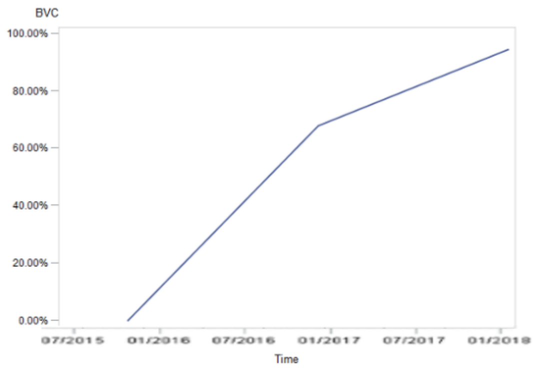
Credit risks

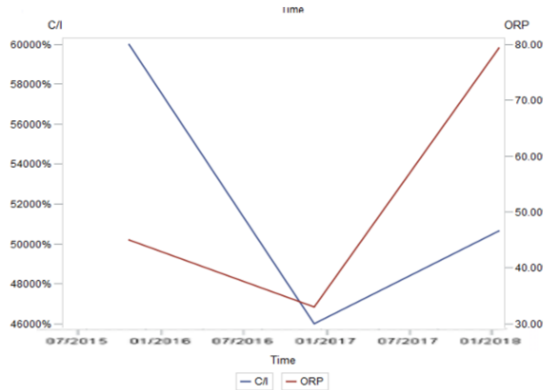
Market risk





Capital and Liquidity risks





Reputational risk

Operational risks

Figure 5.5 Risk performance of Atom

Lessons

Even through Atom has a short history, it developed its risk management system and kept increasing its performance during these years. In general, the risk management performance of Atom remained in a good state. The risk management report in the Atom annual reports suggests a relatively comprehensive approach to its risk management system. In summary, as an example of the UK fintechs, even though they faced a higher credit risk environment, the performance of Atom reflected a good starting point and the development of these fintechs.

5.6 Australia and New Zealand Banking Group (ANZ)

As one of the largest and most influential traditional banks in Australia, ANZ was established in 1835 and had over a 180-year history. Its balance sheet was $897.3bn in size, its equity was $59.1bn, and it had 44,896 employees at the end of 2017 (ANZ, 2019).

Development of ANZ

As ANZ has a long history, similar to HSBC, there is much to recall with all its development. Because of the global operations of the ANZ and the impact of the last financial crisis, we focused more on its development after the last financial crisis. The last financial crisis showed limited impacts on all Australian banks, including ANZ. During the period of the financial crisis, it was still increasing its investments. As the Asian economy developed, ANZ invested a lot in Asia. For example, during 2007-2010, it provided a 20% investment in China's Tianjin Commercial Bank, opened its tenth branch in Vietnam and open sub-branches in Shanghai, China and Nagoya, Japan. After a series of investments in Asia, it received licences from several different Asian countries. For example, it received a retail RMB license from the China Banking Regulatory Commission (CBRC) in 2012 and became the first Australian bank to receive this. At the same time, it received many service awards demonstrating its proper operations.

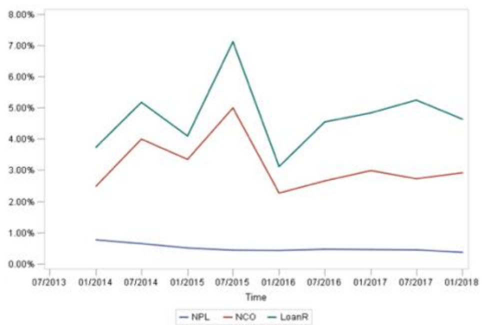
Risk management development

With the long history of ANZ, similar to other traditional banks, annual reports provide a relatively well-established risk management approach. In particular, for ANZ, its risk management framework includes two pillars. One is the risk appetite statement, which is for the board's members who can then prepare strategic objectives and business plans with the risks. The other is the risk management statement which shows the policies from the board and strategy that is based on each risk the bank faces. It provides details on how ANZ identifies, evaluates, monitors, reports, controls and mitigates these risks.

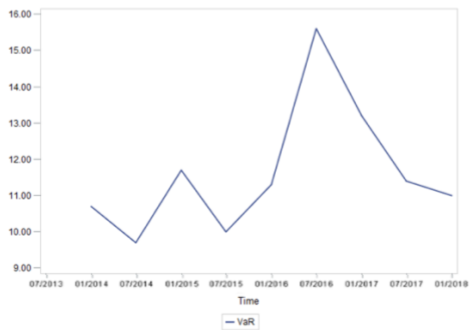
Risk management performance for ANZ is shown in Figure 5.6. In more detail, the credit risk management of ANZ provided a relatively higher level of credit risks than ICBC and HSBC. The trend of the credit risks shows a smooth, slightly increasing line. This confirms the results found in our quantitative analysis that Australian traditional banks, including ANZ, need to pay more attention to credit risks. The potential credit risk of Australian banks was higher than in the other two countries. With respect to market risk, similar to ICBC, the VaR of ANZ showed a low level of impact.

With regards to the capital and liquidity risks, LCR and T1 passed the Basel requirements. This suggests that ANZ had enough liquidity and capital to prevent bankruptcy. With regards to debt level variables, on the other hand, D/E showed an increasing trend. As ANZ was looking for development opportunities in other countries, some of the debt increase could be expected and accepted. However, ANZ still needs to pay attention to its debt level because too much debt may cause severe consequences to its operations. For the reputational risks, the brand value of ANZ generally increased during the investigated time period, but the increasing level decreased. This shows a higher risk potential for Australian traditional banks, including ANZ.

Finally, with regards to the operational risks, ANZ showed a controllable efficiency with a medium level of cost in three investigated countries. Moreover, there were signs of increasing trends in the operational risk variables for ANZ. Thus, managers need to monitor and reduce costs and issues occurring during operations to achieve better management efficiency.

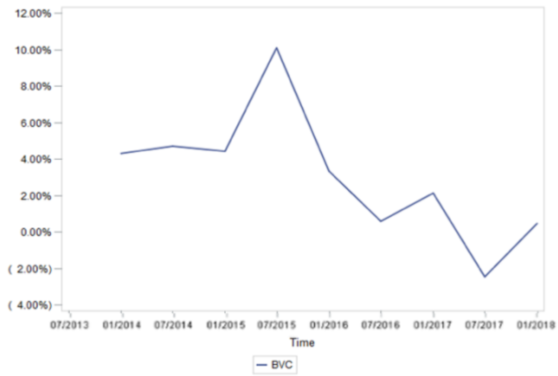


Credit risks

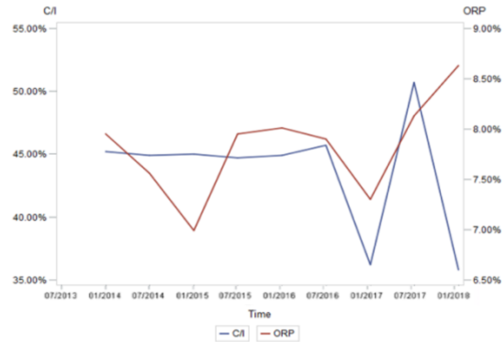


Market risk

Capital and liquidity risks



Reputational risk



Operational risk

Figure 5.6 Risk performance of ANZ

Lessons

In summary, the risk management of ANZ reflects the general performance of Australian traditional banks. Compared with the other two countries, Australian banks need to concentre more on risk management to prevent future financial crises.

5.7 Tyro Payments (Tyro)

Tyro is the largest Electronic Fund Transfers at Point-of-Sale (EFTPOS) provider in Australia fintechs. It was founded in 2003 and received its bank licence in 2005. Tyro aims is to provide businesses with accessible banking services. At the end of 2017, it reached $148m in assets and $93m equity with only 371 employees (Tyro, 2018).

Development of Tyro

Tyro is a fintech that aims to build a more technological and smart way of applying bank services. In 2005, it became the first fintech to receive a bank licence in Australia. In 2011, it became the first one to be certified by new payment regulations regarding the security of payment applications. In 2015, it developed a cloud-based and phone core banking platform. In 2018, it became the first bank to launch low-cost routing payments, deliver integrated Alipay solutions, and implement payments via Siri. At the same time, even though it had a short history, it developed a lot and received many awards. For example, it received the Best Banking Innovation Finder award in 2018 and 2019 and the Best Payment Services Bank in Australia awards in 2018 (Tyro, 2019).

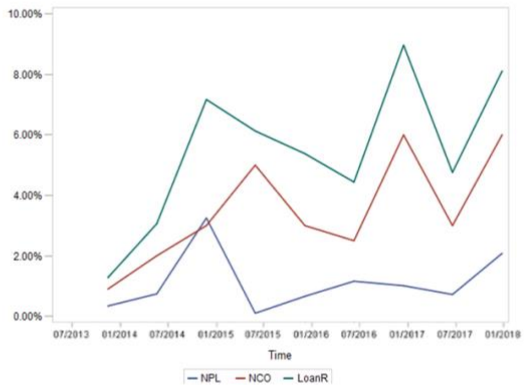
Risk management development

As a fintech, Tyro aimed to manage the risks in its operations. However, it did not provide a separate risk report in its annual report for analysis. The various risks Tyro faced are shown with different variables in the annual reports.

In Figure 5.7, the credit risk variables show an increasing trend. This indicates an increasing default level and a decreasing credit risk management efficiency of Tyro. Combined with the results showed in Section 4.5.5, this shows that both traditional banks and fintechs in Australia need to reduce their credit risks or at least control them to a smooth level. For market risks, the VaR of Tyro showed a higher value than our other chosen fintech cases (e.g., YRD and Atom), showing that Tyro is exposed to more risk within the market.

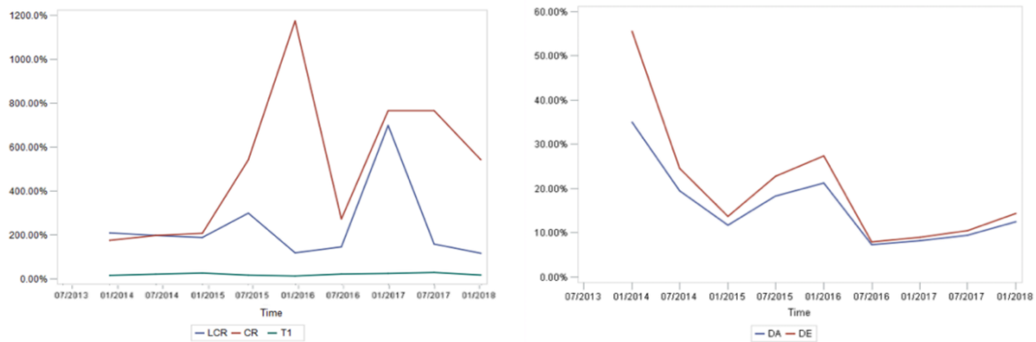
With regards to capital and liquidity risks, with receiving round-up investment, its liquidity level stayed relatively high. Thus, we need to give Tyro more time to stabilise its liquidity level. Moreover, T1 showed a stable trend over the investigated time period and passed the Basel Accords requirement. With regards to debt level variables, both D/A and D/E presented a decreasing trend. This suggests that Tyro controlled debt levels while developing. Similar to other fintechs, Tyro increased its brand value during the investigated time period.

Finally, with regards to operational risks, C/I showed increasing trends, while ORP showed a relatively stable trend. This result indicates a low operational efficiency for Tyro. It is suggested that managers should pay more attention to controlling loss and reducing issues during operations.

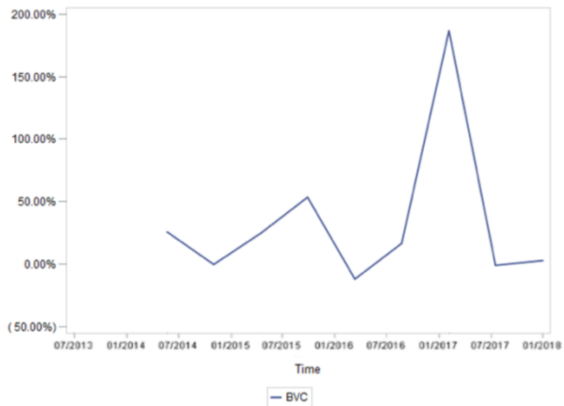


Credit risks

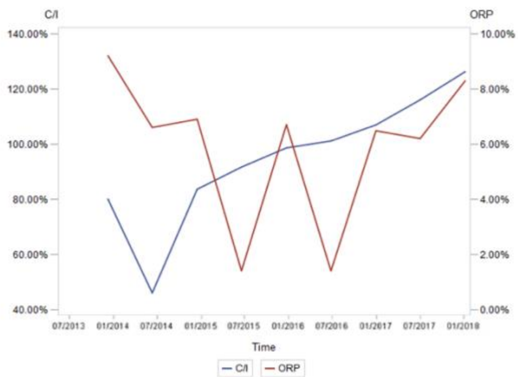
Market risk



Capital and liquidity risks



Reputational risk



Operational risks

Figure 5.7 Risk performance of Tyro

Lessons

In summary, the risk management of Tyro performed not as well as expected. Thus, managers might need to focus more on its risk management, perhaps building a risk report into its annual analysis and building management systems for different types of risks. With the results found from our quantitative analysis, the same suggestions could apply to other Australian fintechs.

5.8 Case studies comparisons

Based on the analysis of each case, in order to have an aggregate view for our case studies, Table 5.1 summaries the similarities and differences between these cases. One bank of each type in each country was selected. Then, our cases showed that all samples of traditional banks had their separate risk report in their annual/interim reports and had already joined the share market. However, not all fintechs cases had a separate risk report in their annual/interim reports. It might be a good suggestion that these fintechs could build a risk report into their annual/interim reports. A risk report could show a clearer view of risks faced by the fintechs, and managers could monitor and reduce those risks with a higher priority. In addition, only the Atom was not on the share market during the investigating time. As noted in Section 5.5, the Atom is in the pre-IPO stage and could join the share market in a short time.

With regards to risk management, similarities and differences can also be found. In more detail, for the credit risk variables, the cases of the Chinese and the UK banks indicated an increasing efficiency of credit risk management with the decreasing trend of these variables. However, cases in Australia showed a slightly increasing trend of credit risks. This confirms the results in Section 4.4. Managers in Australian banks should pay more attention to credit risk variables than the other two countries. For the market risk variables, the cases of the Chinese and Australian banks showed an increasing trend, where the UK cases showed a decreasing trend. This suggests that managers of Chinese and Australian banks should consider more their VaR values during market risk management. Moreover, because of the impacts of the financial crisis and a high exchange rate value, the UK banks had relatively high VaR values. Even though the trend shows signs of decreasing, this result suggests that managers still need to pay attention to the VaR level during risk management. With regards to liquidity and capital holding variables, cases in traditional banks showed an increasing trend with values higher than 100% in LCR and 6% in T1, which suggests that these cases followed legal requirements to hold enough liquidity and capital to prevent bankruptcy. Moreover, similar to traditional banks, the cases were chosen for fintechs also showed a relatively stable situation. However, fintechs need to increase their holding levels of liquidity and capital and meet the legal requirements. With longer operations and more investments, higher values of these variables could be expected. For the debt level variables, our chosen cases for fintechs showed an increasing trend which could be accepted because these fintechs were in the developing stage. Our cases for traditional banks, on the other hand, showed a relatively stable trend. This could be explained by the fact that the business costs of these cases were relatively stable based on their long history.

With regards to reputational risk variables, because each bank had its own operational strategy and performance, BVC showed differences between cases. In general, the brand value was maintained for traditional banks and increased for fintechs. Finally, for operational risk variables, cases in traditional banks showed a stable trend with lower values than fintechs. This suggests that traditional banks had more efficient control over operational risks with a well-established operational risk management system. The chosen fintechs, on the other hand, showed a relatively poor performance in operational risk management. All of them had the situation of cost more than income during the investigated time period. Thus, fintechs should pay more attention to control their operational costs to achieve better efficiency. In particular, the operational efficiency of Tyro reduced during the investigated time period, so managers in Tyro should take extra care of its operational risks. If they failed to control their costs and issues in operations, business failures could happen.

	ICBC	YRD	HSBC	Atom	ANZ	Tyro
Location	CN	CN	UK	UK	AUS	AUS
Bank type	T	C/F	T	C/F	T	C/F
Have risk report in annual report	√		√	√	√	
In a share market	√	√	√		√	√
Credit risk variables (NPL, NCO and LoanR) trend	-	-	-	-	S/+	+
Market risk (VaR) trend	+	+	-	-	+	+
Liquidity holding variables (LCR and CR) trend	S	+	+/S	S/+	+	S/-
Debt level variables (D/A and D/E) trend	S	+	S/-	+	S/+	+
Capital holding variable (T1) trend	+	S	+	S	+	+
Reputational risk variable (BVC) trend	+	-	S	+	-	S
Operational risk variables (ORP and C/I) trend	-	-	S	S/+	S/-	+
C/I >1 exists		√		√		√

Table 5.1 Similarities and differences in case studies

Notes: 'T' represents traditional bank; 'C/F' represents challenger bank/fintech.
'+' represents positive trends; '-' represents negative trends; 'S' represents stable trends.

In summary, through the case studies, we saw the different risk management performance and strategies of these banks. The results were consistent compared with the results obtained from our quantitative analysis. The overall results were more comprehensive through adding the qualitative analysis. With regard to types, traditional banks had more efficient risk management than fintechs. With regard to countries, Chinese banks had a more stable performance than the other two countries. Having recovered from the impacts of the last financial crisis, UK banks developed relatively well, and the efficiency of risk management was increased in the investigated time period. Australian banks had a relatively good performance during the investigated time period. However, because of their higher failure potential in risk management than the other two countries, the future performance of Australian banks is more concerning. Similar to Brigham and Ehrhardt (2014), the case studies showed the importance of risk management. Thus, in order to have better future performance, managers should pay more attention to risk management, and should analyse and prioritise risks by types and variables.

5.9 Conclusion

The case studies in this thesis represent a brief introduction into some illustrations of representative cases for our three countries and two types of banks. They highlight some of the themes from earlier sections. Viewed in aggregate, they provide reasonable explanations of the risks that different banks face and a few strategies as to what should be done for better risk management. The fact is that risk exists in all banks, all countries, and every institution at all times. Risks cannot be solved through a high liquidity position or capital strength. However, these may provide better adaptability for banks when facing these risks. By facing the global crisis, proper risk management could set the 'survivors' apart from the 'failures'. Fragile risk management system collapses spectacularly like some banks that shut down during the financial crisis even though they performed quite well before the crisis. This suggests that a bank with weak risk management may only operate in stable markets. When the market falters, it cannot handle the market movements.

This section listed one bank of each type in each country to show their risk management performance during the investigated time period. Interestingly, they showed different performance levels. For example, given the strength of the Chinese economy, banks in China developed a lot. At the same time, with the higher involvement of the government, the risk management of Chinese traditional banks was in a relatively good state. For

Chinese fintechs, their risk management showed a better trend as time developed. With the high impact of the last financial crisis in the UK, both types of banks in the UK showed similar risk levels, and with their risk management strategies, the risk levels seemed to reduce as time developed. For Australian banks, as they were untouched by the US subprime loses, the impacts of the financial crisis were limited, and these banks remained in a healthy and profitable state. However, they were not without their crises and issues. Indeed, both types of banks showed a lower risk efficiency, which might cause difficulties for the future risk performance of the Australian banks.

In summary, risk cannot vanish. Risks have to be taken. For example, shareholders take a risk when buying shares in the hopes that they will be compensated sufficiently. Risk also has to be managed. There is no magic formula to choose the right risk management strategy. Risk management needs more attention from bank managers. They need to identify which risks their bank faces and how to prioritise these risks. One possible solution for them could be to look at the models built in this thesis.

CHAPTER SIX

DISCUSSIONS

6.1 Introduction

In the previous chapters, risk variables and their impacts on bank performance in different countries and types were listed and analysed. This chapter serves as a follow up to the general discussion on the banks' risk management strategies. The emerging results of the bank risk management strategy will be discussed in this chapter, and strategic suggestions for each type of bank will be applied. The strategic suggestions were theorised from the case studies and detailed analysis of panel data regression models of each country and type of traditional bank and fintechs. It is hoped that these suggestions combined with regression models will provide better perspectives in risk management on traditional banks and fintechs and provide an academic basis for fintechs as they are a developing area in the banking industry.

6.2 Triangulation comparisons

Before providing the suggestions for both types of banks, we summarise the similarities and differences between all three countries in both types of banks based on the results of random-effects estimates, GMM estimates and case studies. The results are presented in three tables based on countries and types. With regards to similarities, there are catalogued based on country (Table 6.1) and type (Table 6.2). With regards to differences, Table 6.3 shows the different impact levels for each country based on significance levels and coefficient values of the risk variables (1 for the lowest, 2 for the medium, and 3 for the highest).

For traditional banks	
All three countries	1) Credit risks have negative impacts on bank performance (ROA, ROE & EPS); 2) Market risk has a negative impact on ROA & EPS; 3) Higher liquidity holding levels (LCR & CR) suggest a better bank performance (ROA, ROE & EPS); 4) T1 has a positive impact on bank performance (ROA, ROE & EPS); 5) D/A and D/E have a negative impact on the banks' performance (ROA, ROE & EPS); 6) Reputational risk variable (BVC) has a positive influence on ROE and EPS; 7) Operational risks have negative impacts on bank performance (ROA, ROE & EPS).
China & UK	(1) Bank size has a negative impact on ROE.
China & Australia	(1) Market risk has a negative impact on ROA, ROE & EPS; (2) Reputational risk (BVC) has a positive influence on ROA, ROE & EPS.
UK & Australia	(1) Bank size has a positive impact on ROA & EPS.
For fintechs	
All three countries	a) Credit risks have negative impacts on bank performance (ROA, ROE & EPS); b) Market risk has a positive impact on ROE, but a negative influence on EPS; c) Higher liquidity holding levels (LCR & CR) suggest a better bank performance (ROA, ROE & EPS); d) T1 has a positive impact on bank performance (ROA, ROE & EPS); e) D/A has a negative impact on bank performance (ROA, ROE & EPS); f) Reputational risk (BVC) has a positive influence on ROA, ROE &EPS; g) Bank size has a positive impact on ROA, ROE & EPS; h) Operational risks have negative impacts on bank performance (ROA, ROE & EPS).
China & UK	No additional similarities.
China & Australia	(a) Market risk has a negative influence on ROA & EPS, but a positive impact on ROE; (b) D/E has a positive impact on EPS.
UK & Australia	(a) D/E has a negative impact on ROA & ROE.

Table 6.1 Similarities between countries

China
♦ Credit risks have negative impacts on bank performance (ROA, ROE & EPS); ♦ Market risk has a negative impact on ROA & EPS; ♦ Higher liquidity (LCR & CR) and capital holdings (T1) suggest a better bank performance (ROA, ROE & EPS); ♦ D/A has a negative impact on ROA, ROE & EPS; ♦ Operational risks have negative impacts on bank performance (ROA, ROE & EPS).
UK
♦ Credit risks have negative impacts on bank performance (ROA, ROE & EPS); ♦ Market risk has a negative impact on EPS; ♦ Higher liquidity (LCR & CR) and capital holdings (T1) suggest a better bank performance (ROA, ROE & EPS); ♦ D/A and D/E have a negative impact on ROA, ROE & EPS; ♦ Bank size has a positive impact on ROA & EPS; ♦ Operational risks have negative impacts on bank performance (ROA, ROE & EPS).
Australia
♦ Credit risks have negative impacts on bank performance (ROA, ROE & EPS); ♦ Market risk has a negative impact on ROA & EPS; ♦ Higher liquidity (LCR & CR) and capital holdings (T1) suggest a better bank performance (ROA, ROE & EPS); ♦ D/A has a negative impact on ROA, ROE & EPS; ♦ D/E has a negative impact on ROA & ROE; ♦ Operational risks have negative impacts on bank performance (ROA, ROE & EPS)

Table 6.2 Similarities between bank types

		CN	UK	AUS	CN	UK	AUS	CN	UK	AUS
		ROA			ROE			EPS		
T	Credit risks	1	2	3	1	2	3	1	2	3
	Market risks	1	3	2	2	1	3	1	2	3
	Liquidity risks	2	3	1	3	1	2	1	2	3
	Capital risks	1	2	3	2	1	3	1	2	3
	Debt level risks	1	3	2	2	3	1	1	2	3
	Reputational risks	1	3	2	1	2	3	1	2	3
	Bank size	2	3	1	1	2	3	1	3	2
	Operational risks	1	3	2	3	2	1	1	2	3
C/F	Credit risks	2	3	1	3	1	2	3	2	1
	Market risks	2	3	1	2	3	1	3	2	1
	Liquidity risks	1	3	2	2	3	1	1	3	2
	Capital risks	1	2	3	2	1	3	3	2	1
	Debt level risks	2	3	1	3	2	1	2	3	1
	Reputational risks	1	2	3	1	2	3	2	3	1
	Bank size	3	1	2	3	2	1	1	3	2
	Operational risks	2	3	1	1	3	2	2	3	1

Table 6.3 Differences in impact level between countries

Notes: 'T' represents traditional bank; 'C/F' represents challenger bank/fintech.
'CN' represents China; 'AUS' represents Australia.

As shown in the tables above, the first similarity is that all credit risk variables negatively impact on both types of banks for every investigated country. However, the level of impact is different. For example, as noted in Sections 4.2 to 4.5, they show a much higher impact of credit risk in fintechs than in traditional banks except for the EPS in Australian banks. In addition, for traditional banks, credit risk shows a bigger influence on UK banks than in other countries in ROA and ROE. The possible reason for this is that the last financial crisis had more impact in the UK than in the other two countries. For fintechs, the overall highest impacts of credit risks were seen in the

Chinese fintechs. As they are still in the starting stage of operations, they should be given more time to develop and operate, which could show better results. However, with an increasing trend and a relatively strong influence, Australian banks need to be more concerned about credit risk management than the banks in other countries.

Next, market risk has a generally negative impact on bank EPS, which suggests that if banks face strong influence shown in market movement, their performance will not be as good as in a smooth market environment. However, some of the fintechs may find opportunities with market movements to increase their returns in assets and equity. Thus, they need to balance the VaR values as the high market risk will lead to a weak EPS but might increase ROA or ROE. The third overall similarity is that LCR shows a positive influence on both types of bank in all three countries. This suggests that with the Basel requirements after the last financial crisis, this variable could reflect the liquidity situation of the banks. The higher the LCR, the better the performance of the banks will be. Moreover, the same situation happens with T1, as to meet the required level of the Basel could help banks have enough capital to prevent bankruptcy. The next similarity is about D/A and D/E, which reflects the ratio of the banks' debt level to their assets and equity. Our findings suggest that traditional banks need to control their debt level to achieve better performance. For fintechs, as negative equity exists, they need to develop their asset level to be higher than their liabilities, then keep the debt level healthy to achieve better performance.

Furthermore, as fintechs are in their starting and developing stage, an increase in their assets can reflect better performance. However, as the large traditional banks have been developed for a long time, keep their assets at a stable level and reducing some non-necessary assets could help their performance. Finally, with regards to the operational risks, there also shows a negative impact on performance in each country and type of bank. In more detail, for traditional banks, the critical thing to avoid is extreme operational risk issues that could disrupt operations. However, fintechs face different operational risks. Dongrong Li, the president of China Internet Finance Association, said that the most critical operational risk face by fintechs is 'the safety of the business'.

For example, fintechs need to identify the customer to avoid fraud during operations, where traditional banks could avoid this issue through face-to-face operations (ABTnetwork, 2018). As operational risks are hard to monitor, managers in both types of banks have to control cost levels to maintain better efficiency.

6.3 Strategic suggestions for risk management

With developing of banking industry, the understanding of the risk management of banks has improved substantially. Much has been written on the influence of risk management to bank performance, both in the academic literature and in the financial press. However, with the keeping developing of technology, a new type of banks called challenger banks/fintech established and competed with the traditional banks. As both traditional banks and fintechs are in the risk business in the process of providing financial services. In this thesis, we selected five main types of risks face by banks and analysis their influences on traditional banks' or fintechs' performance. Based on the results in Chapter 4, 5 and Section 6.2, we have found that managers should have different focuses when managing risks for different types of banks in different countries. In order to highlight the different situation in each country, to prioritise these risks become an essential strategy to help managers to control these risks. Thus, this section discusses the corresponding strategies for different types of banks in different countries and draws together some risk management recommendations for the banking industry.

For Chinese traditional banks, managers should make sure the bank meets the capital and liquidity requirements of the local and global regulations. Next, they need to control their debt to a reasonable level. Thirdly, managers should monitor their performance in credit operations, which needs to operate smoothly and prepare enough provisions for credit risk occurring. At the same time, operational risk issues need to be monitored to keep them in the least damaging situation, which could also help the bank stay healthy. Together with their stability in the market, this will lead to good performance. The suggestions for the UK traditional banks are similar to Chinese traditional banks. With the increasingly improved efficiency of risk management, managers should continue this to achieve better future performance.

However, Australian traditional banks show more potential for risk management failure. To prioritise these risks makes more sense to help Australian banks achieve better future performance. In more detail, firstly, managers in Australian traditional banks need to monitor the credit risk level when they do credit-related business, as in the investigated period, their risk levels increased. Next, managers also need to cut unnecessary operational costs and reduce the chance of operational risks occurring to achieve a low operational risk level, as this also showed an increasing trend during the investigated time. Besides that, Australian traditional banks need to take extra care about their capital and liquidity holding levels, as their risk levels show an increasing trend. If there is not enough capital and liquidity prepared, the banks will be in trouble.

For Chinese fintechs, managers should firstly keep their credit operations smooth and at a lower risk level. Next, they need to be alert to the risks of the market. Also, during operations, managers should make sure the fintechs meet or try to meet the regulatory requirements for liquidity, capital and debt level. Particularly, they need to control their costs in operations, especially for operational risks. Thus, with the development of fintechs, their assets and brand values will increase, and they will achieve better performance. The suggestions for fintechs in the other two countries are also similar to the above for the Chinese fintechs. Moreover, Australian fintechs, similar to Australian traditional banks, need to pay more attention to manage these risks. They suffered less in the last financial crisis, but their risk levels show a higher potential for future failure.

Therefore, banks could increase their management efficiency and achieve better future performance by prioritising the risks during risk management. Also, based on the models this research has built, managers can predict future bank performance through their history of risk management performance. By paying more attention to risk management, future performance can also be predicted to be better. Moreover, managers should follow local and government legalisations and try to meet the regulatory requirements, which could increase the chances of good performance in the industry.

In light of the above, besides considering the types and location of the banks, managers in both traditional banks and fintechs could implement risk management strategies in the following four ways:

1. Managers could set standards and build financial reports for risks. Most traditional banks have already implemented this strategy, but not fintechs. Thus, fintechs' managers should implement this strategy as soon as possible. Moreover, this should go beyond public reports. Internal reports could be prepared for managers more frequently, which could help them better understand the risks faced by the bank or fintech.

2. Managers should clearly understand their position limits and rules when they are making risk-related decisions. This strategy could restrict the individual and overall risk faced by managers and the bank or fintech. For example, senior managers could prioritise different types of risks and allocate resources, while line managers might just focus on one particular type of risk.

3. When managers plan for future investment guidelines or management strategies, they need to consider their historical and current risk positions. Based on our models, managers could predict the future performance of the bank or fintech by filling in their current and historical risk data. Thus, following this strategy, managers could make a more appropriate decision for the organisation.

4. Managers could build and enter incentive schemes. This strategy could encourage all staff to focus more on risk management, which could help banks and fintechs to perform better.

Besides managers, our analysis can also benefit shareholders and investors. They can estimate the future performance of fintechs or traditional banks they are interested in based on our models to test whether they are worth investing in. Table 6.4 provide a selection process for investors and shareholders. Thus, our analysis allows us to identify banks or fintechs that meet regulatory requirements, have improved trends in risk management and performance, and are supported by local governments that could have better performance and be more worthy of investment.

For shareholders and investors who would like to test whether a bank/fintech developed	For shareholders and investors, who would like to select between two or more banks/fintechs
1. Search from official website to download the historical annual/interim reports;	
2. Find relevant variables in our models;	
3. Calculate the average value and estimated value for the next year;	
4. Put data in the models for the bank or fintech located and get results;	
5. If the performance better than the current year or the average value, invest it.	5. Select the best or better performed banks or fintechs, then invest.

Table 6.4 Investment process for shareholders and investors

Based on the risk insights gained from Chapter 4, besides managers, investors and shareholders, our analysis could also help governments and policymakers to build a strategic plan for banks and fintechs. Firstly, similar to investors and shareholders, governments and policymakers could use our models to test the performance of traditional banks and fintechs. Instead of investing in them, governments and policymakers can use our models to identify banks/fintechs appear risk management and performance problems. This helps policymakers monitor the 'problems' more quickly and support or shut the 'problems' down at the right time. Secondly, governments and policymakers need to make more targeted regulatory requirements based on bank type. For example, we found that credit risk influences the performance of fintechs more than traditional banks, and fintechs had a larger credit risk than traditional banks in all three countries. However, there are no particular credit risk variables requirements during investigating time period. Fintechs have to follow the same requirement as traditional banks, which might be too tight for them. Thus, governments and policymakers should make a more targeted requirement for credit risk variables for fintechs, giving them more time to survive in the beginning stage. Thirdly, through our triangulated comparisons, we found that banks/fintechs perform better in a more stable financial environment. Therefore, our analysis can encourage the government to provide a better financial environment for the banking industry. In summary, Figure 6.1 shows a diagram of the strategic plan for risk management, including bank managers, investors and policymakers.

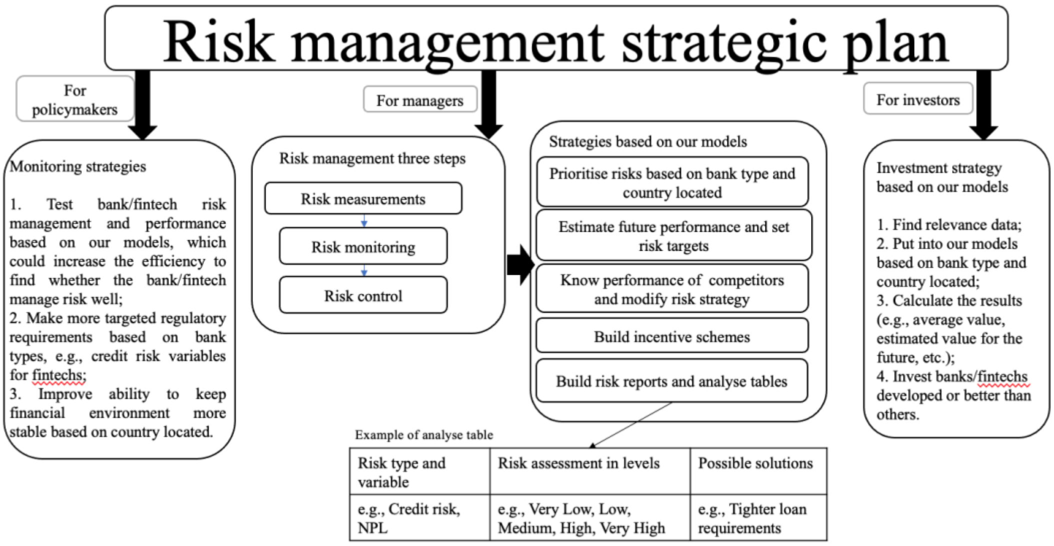


Figure 6.1 Risk management strategic plan

Furthermore, combined with the analysis of the literature review, we can say that investing in fintechs during and after the financial crisis is a good recommendation. This is because, 1. The 2008-09 financial crisis was one of the triggers for the establishment and development of fintechs; 2. Governments started to support the development of fintechs, while more fintech-related regulations were enacted; 3. More traditional banks started to invest in fintechs or set up fintech-related subsidiaries. In addition, this is still a good time to invest in fintechs. People in many countries and regions have to live and work in lockdown because of Covid-19. As fintechs can offer all financial services online, this crisis gives them an opportunity to capture the market. As a result, our results can provide investment advice for investors and shareholders. For governments and policymakers, our results can give them a better understanding of how risk affects the performance of banks/fintechs. Policy makers can have a greater focus on risk management when they develop policies for fintechs or update those of traditional banks. Also, if local governments want to support any traditional bank or fintech, they can use our analysis as one of the basic ideas to support banks or fintechs or even the whole industry.

6.4 Conclusion

The discussions presented in this chapter highlighted risk management comparisons and their impacts on bank performance between our selected countries. The overall discussion showed that each type of bank in each country had different strategies for managing risks. Based on the quantitative and qualitative approach analysis, each strategy was defined considering not only the bank types but also the risk management efficiency and the country where the bank is located.

In summary, three main conclusions based on investigated countries and four risk management strategies can be drawn for this chapter. With regards to investigated countries, firstly, with the higher involvement and support of the government, the Chinese banks had a relatively good and stable performance. Even for fintechs, the performance could be expected to be better in the future. Secondly, with a higher impact from the last financial crisis, the starting points of both the UK's traditional banks and fintechs were not very good. With a series of improvements in bank management systems and regulations, the risk management and performance in the UK were trending better. Thirdly, because the impacts of the last financial crisis were limited for Australian, a relatively good development was shown in traditional banks and fintechs. However, risks trended to increase, so future risk management and performance should be concerned by regulators and managers. If better risk management rules and strategies could be applied, the crisis might be avoided. However, if risks develop freely when a crisis happens, results could not be estimated. With regards to risk management strategies, in general, these four strategies are established to measure risk exposure, build procedures to manage these risk exposures, limit manager position to an acceptable level and encourage all staff to consider risk during operations.

Thus, a threefold contribution has been built based on this chapter. Firstly, it contributed to current research by presenting comparisons based on empirical data. Secondly, it provided useful insights for managers and researchers on how risk management strategies were deployed. Thirdly, it provided potential strategic plans for managers and policymakers. Based on these observations, the final chapter will provide an overall conclusion for this study, combined with suggestions for future research.

CHAPTER SEVEN

CONCLUSIONS, IMPLICATIONS AND FUTURE WORK

7.1 Introduction

Based on financial technology development and increased global financial connections, customers are shifting their preferred way of receiving financial services and products. Given this situation, fintechs have become new and popular financial institutions that can supply financial services and products through more digital ways than traditional banks. However, fintechs did not perform as well as excepted, and there are still limited studies investigating this area. Thus, how these fintechs performed and why the situation happened was worthy of investigation. In addition, due to the importance of risk management, our research has investigated how risk variables impact bank performance in traditional banks and fintechs. To achieve a comprehensive view in this area, this thesis selected China, the UK and Australia to be the countries for investigation. As a result, this study addressed the current situation and the differences between bank types and countries which could contribute to knowledge.

The findings from this research lead to a set of conclusions and implications for future researchers, banking sector managers and analysts. These conclusions aim to notice the importance of risk management in operating bank performance both in traditional banks and challenger banks/fintechs. It is expected that this will help banks 1. Understand their current situation and performance of risk management. 2. Find the appropriate way to prioritise risks. 3. Provide strategies for managers in risks management to achieve sustainable growth in the banking industry. The following section presents conclusions for each research question. Section 7.3 outlines the contributions and implications of this study to theory and practice. The limitations of this study and indicative future research directions are presented in Section 7.4. Section 7.5 provides an overall conclusion for this study.

7.2 Conclusions for each research question

This research attempted to identify the impact of risk management on the performance of traditional banks and challenger banks/fintechs. It was noted that the importance of risk management and its impact on performance was studied quite a lot for traditional banks, such as Anggaredho & Rokhim, 2017; Bessis & O'Kelly, 2015; Fu & Heffernan, 2009; Geng et al., 2016 and Nakashima, 2016. However, the fintechs' relationship between risk management and performance had only limited investigations. Given this situation, we followed the methodologies of previous studies in traditional banks, applied them to both traditional banks and fintechs, and built four research questions to reach a more comprehensive investigation of risk management and its impacts on performance.

For research question one: '*What are the critical characteristics of bank risk management variables and how can we use them to analyse bank performance through bank data?*'.

We summarised five main risk types (credit risk, market risk, liquidity and capital risk, reputational risk, and operational risk) in management in 12 risk variables, together with the bank size, to represent these banks' risk management. We then used three performance variables to show bank performance. As we collected data through the banks' annual and interim reports, the variables were showing on a semi-annual basis. Thus, to analyse the dataset and show the relationship between variables, panel data regression models were suitable. Moreover, with the F, LM and DWH test, the random-effects approach was more appropriate. As a result, this research applied eighteen random-effects panel regression models to analyse risk management and its impacts on bank performance for both traditional banks and fintechs in three different countries (China, the UK and Australia). In order to have a more robustness results, the GMM estimates were applied and consistent results were shown. Moreover, we presented 6 case studies to show the individual performance in risk management which further showed the robustness of our results from random-effects and GMM estimates.

For research question two: *'What differences are shown between traditional banks and challenger banks/fintechs in their risk management?'*.

Similar to previous studies, we confirmed the importance of risk management in bank performance based on the findings from our random-effects panel data regression models, GMM estimates together with the case studies. The results showed similarities and differences between the two types of banks. For instance, credit risk variables had a negative impact on bank performance for both types of banks. We further found that fintechs should pay more attention to credit risk as they have higher coefficient estimates for the variables. For market risk, fintechs also need to be more alert, as movement will have more impact on their performance. Moreover, sometimes, fintechs could see such movement as an opportunity to earn some returns.

For capital and liquidity risk, both types of banks showed similar results. Both of them need to keep tier one capital stable, increase liquidity levels and reduce debt to a reasonable level, which could help them to achieve better performance. As these variables were required to achieve a certain level by the governments and Basel Accords, banks need to follow regulatory requirements in their operations. Furthermore, as fintechs were in their starting and developing stages, developing their assets can result in better performance. However, for the large traditional banks that had been developed for a long time, keeping assets at a stable level and reducing some non-necessary assets would help their performance. Because random-effects and GMM estimates showed that negative estimated coefficient values existed for ln(asset) for traditional banks.

With regards to operational risks, these also showed a negative impact on performance for both bank types. For fintechs, these variables had relatively high impacts. This indicates a different strategy for the different banks with different coefficient estimates. For fintechs, the most important thing in operational risk management is to have 'a safety business' (e.g., identify the customer to avoid fraud) (ABTnetwork, 2018). For traditional banks, the critical thing is to avoid extreme operational risk issues occurring, which could help operations continue smoothly. As operational risks are hard to monitor, managers in both types of banks have to control cost levels for better efficiency.

For research question three *'What differences exist among our three different countries in risk management and bank performance, and how well did these countries react to the last financial crisis?'.*

Following the previous research question, besides the bank types, similarities and differences also existed between the three countries. For example, in traditional banks, credit risk showed a stronger influence on UK banks than other countries in the investigated time period. One possible reason for this is that the last financial crisis impacted the UK more than the other two countries. However, Australian banks had more potential for credit failure, as their credit risk variables showed an increasing trend.

In fintechs, the highest impacts of credit risks were seen in Chinese fintechs. This suggests a low efficiency of fintechs' credit risk management. However, as these fintechs were established recently, and the Chinese government published a series of regulations on fintechs' operations, by following these, the fintechs showed increased efficiency in credit risk management. Thus, more time should be given to allow better results. In addition, unlike China and the UK, credit risk variables in Australian fintechs showed a positive trend, which suggests there may be risky performance in the future. Thus, both types of banks in Australia should take extra care with credit risk management.

With regards to market risk, this had a more substantial influence on the UK than the other two countries. With its higher level of connections to other countries, the financial crisis heavily impacted the UK. Another overall similarity for all countries was LCR which showed a positive influence on bank performance. As noted above, this suggests that both traditional banks and fintechs should follow the legal requirements, which could help them to achieve better performance. In addition, with regards to operational risks, we saw that operational risks heavily influenced Australian traditional banks and the UK fintechs. As these banks had relatively higher operational risk costs, they should keep monitoring their operating activities to reduce risk. If they fail to do so, the performance would be negatively affected.

For the last research question *'through our analysis, what should these banks/fintechs do to improve risk management for future challenges?'*.

In both our quantitative and qualitative results, we showed the necessity of prioritising these risks based on the type of banks and the country where the bank is mainly located. Through prioritising the relevant risks during risk management, banks could increase their management efficiency and achieve better performance in the future. Besides prioritising different types of risks based on bank type and locations, we provide four more suggestions for managers to both traditional banks and fintechs. Firstly, managers should build reports and set standards for risks. For fintechs, they could follow or gain experience to build risk reports and standards like traditional banks. For traditional banks, they should apply this strategy beyond public reports. They could build more frequent internal risk reports (e.g., daily or weekly) to help managers better understand risk. Secondly, risk managers in both types of bank need to understand their position limits and rules clearly. Thirdly, when managers plan for future investment or management strategies, they need to consider their historical and current risk positions. For example, they could use our model to estimate future performance and test how performance is likely to change if they apply a new strategy. Fourthly, managers could build and join incentive schemes, which could make all staff in the bank or fintech consider risk management more.

As noted in Chapter 4, fintechs should pay attention to credit risk first. Even as they try to attract more customers, the quality of any credit activities should be controlled. For traditional banks, they should make sure that their liquidity, capital and debt are at a healthy level because the subprime crisis caused the traditional banks to become short of liquidity, which led to severe outcomes. On the other hand, based on the banks' locations, as the UK banks suffered a lot during the last financial crisis, the risk management performance follows a better trend with a healthier level for each of the risk variables. With a high involvement from government and the increasing trend of the economy, Chinese traditional banks performed relatively well. However, for the

Australian banks, as the last financial crisis had a limited influence on their performance, the risk management of Australian banks provided decreased efficiency. This was a warning sign for managers to pay more attention to risk management during their operating activities. If they do not consider risks carefully and increase risk management efficiency, performance could deteriorate in the future.

The analysis shows that the 2008-09 financial crisis had a different impact on traditional banks in different countries. After the last financial crisis, challenger banks/fintechs started to be established and became a hot topic in the banking industry. According to the literature review in Chapter 2, we note that the last financial crisis was one of the triggers for the establishment and development of fintechs. For example, we found that after the last financial crisis, governments started to support the development of fintechs. Meanwhile, as more fintech-related regulations were enacted, more traditional banks started to invest in fintechs or establish fintech-related subsidiaries. Therefore, we can say that investing in fintechs during the financial crisis is good advice for shareholders, managers and investors related to the banking sector. Furthermore, our results show that the performance of most fintechs improved during the investigated time period. Although our sample only tested surviving fintechs, the results remain robust through both quantitative and qualitative analysis. As noted in Chapter 6, our models could help investors to reduce the probability of choosing failed fintech, because if the selected fintech perform well in our models, it will not be easily to fail. Therefore, for shareholders, managers and investors interested in investing in fintechs, they can choose those fintechs that meet regulatory requirements, have developed trends in risk management and performance, and are supported by local governments. In addition, it is still a good time to invest in fintech. As a result of Covid-19, people in many countries and regions have to live and work under lockdown. As fintechs offer all financial services online, this crisis gives them an opportunity to capture the market. Therefore, people interested in investing in fintechs can search for reports from the official websites of fintechs and statistical websites published by governments to see how these fintechs have performed in risk management and returns over the years. Also, they can use our models to estimate the future performance of their target fintechs to test whether it is worth investing.

7.3 Contributions and implications for theory and practice

The objective of this thesis is to contribute to knowledge in theory and practice. Through our literature review, some of the research gaps were identified, namely that there was an absence of investigation in risk management in fintechs and their comparisons with traditional banks. We have critically investigated and evaluated the chosen topic. This section shows how the results from this research fill the related gaps in knowledge, thereby contributing to theory and practice. Table 7.1 summaries our key contributions to knowledge.

RQ	Contributions to knowledge
1	**Theoretical:** This research contributed to the theory and perceptions of bank risk management, fintechs' development and financial performance improvement in China, the UK and Australia. It demonstrated risk management's impact on banks' performance and how they improve the efficiency of risk control, profitability and growth in fintechs as well as traditional banks. The results highlighted the focus points when managing these risks, the efficiency of risk management and their effects on bank performance, in order to assist future studies. The results showed that each type of risk shows its impact on bank performance at a different level through different variables. Moreover, as three countries and two types of banks were investigated, based on the country's situation, it presented the similarities and differences between countries and between bank types. Further, we followed previous quantitative methods (random-effects estimates and GMM estimates). Both of the quantitative analysis showed consistent results. Together with the case studies, this research showed

	more comprehensive results in the area. Thus, this thesis could enhance the analysis in risk management for different types of banks. **Practical:** We demonstrated the main risks faced by traditional banks and fintechs and how the associated variables influenced bank performance. This research informed managers about what risks influence bank performance. Moreover, we highlighted the development of the fintechs where not much research had existed, especially in risk management for fintechs. We also built statistical models that could help managers improve their understanding of risk management through statistical analysis methods.
2	**Theoretical:** We theoretically applied insight into the different risk variables on bank performance via different ratios through random-effects estimates and GMM estimates. We applied a bigger model by combining five different types of risks, which extends knowledge of bank risk management, performance and the relationship between them. This research was applied to different types of banks. Moreover, two types of models, together with case studies, were applied to show the robustness of the results. Thus, this research offered theoretical development regarding risk management and banks' performance in different types of banks. **Practical:** The demonstrated factors showed how banks could use these panel data regression models to understand financial performance better. Moreover, as the differences were shown in this research between types of banks, they would help banks and fintechs understand the different focus points when managing their risks, thereby prioritising risks and creating a better

	performance to attract customers. We established comparisons between bank types which can help them better understand themselves and their competitors. For example, we found out fintechs should consider credit risks more than traditional banks, because they have higher significance levels and coefficient values with credit risk variable. Thus, fintechs need to improve their credit risk management, such as build credit risk reports and detailed credit risk standards. Further, we also encouraged better risk management efficiency and a healthy competitive environment.
3	**Theoretical:** As noted above, besides the type of bank, we also considered the countries where these banks reside. We highlighted the differences and similarities shown between the three countries (China, the UK and Australia). We extended the knowledge of banks in different countries when managing their risks. We showed how these risk variables influence bank performance in different countries and made further suggestions for managers in the risk management process. It extended knowledge of risk management at the country level, which should be helpful for future testing in the global banking system. **Practical:** We revealed attributes affecting different types of banks based on different countries and that their strategies to improve efficiency have different focus points. For example, credit risks and operational risk trends were increased in Australian banks. Combined with the results of our random-effects estimates and GMM estimates, we showed that Australian banks should be worried about future performance more than the other two countries, which were showing a decreasing trend of risks. Thus, managers in Australian banks should pay more attention to risk management activities during their operations.

4	**Theoretical:** We integrated panel data regression models (e.g., random-effects estimates and GMM estimates) and case studies related to risk management and its impact on bank performance. We analysed results for two types of banks (traditional banks and challenger banks/fintechs) in three countries (China, the UK and Australia) which contributed to the banking system theory about fintechs. We corroborated different risk management strategies which should apply to different types of banks and countries. We provided a broad insight into bank performance in improving risk management efficiency with different types of banks from three countries. This contributed to risk management theory in new types of bank fintechs. In addition, We compared the results with those for traditional banks, which further extended the theory of risk management in banking operations. We also compared the results between three selected countries, which further extended risk management theory based on bank locations. **Practical:** We developed an integrated analysis for improving risk management efficiency and bank performance. This could help the banking industry develop a better awareness of fintechs. We also provide suggestions based on types of banks that could help managers prioritise the risks they face and predict banks'/fintechs' future performance based on our models. We also applied suggestions and plans in risk management strategies for managers in both types of banks and three countries. Moreover, we provided suggestions in investing in fintechs for people interested.

Table 7.1 Contributions to knowledge for each research question

We contributed to knowledge by helping to fill the gaps in fintechs development, risk management, their impacts on bank performance and the current situation shown in traditional banks, especially with respect to how Chinese, the UK's and Australian banks performed. We developed a better understanding of the differences and similarities between traditional banks and challenger banks and fintechs among these countries with respect to risk management.

In summary, this research could provide different understandings and suggestions for different types of people interested in the banking industry. For banks' and fintechs' managers, our results showed the necessity of prioritising these risks based on the type of bank and the country where the bank is mainly located. Through prioritising risks, banks and fintechs could improve their management efficiency. Besides prioritising different types of risks based on bank types and locations, we also provide four risk management suggestions to both types of banks in all three countries. Firstly, managers should build risk reports and set risk standards on a more detailed and frequent basis. Secondly, managers need to understand their management limits and rules clearly. Thirdly, managers need to consider the bank's/fintech's historical and current risk position when planning investment and management strategies. Fourthly, managers could build and join incentive schemes, which could increase the enthusiasm for participation in risk management. For investors or shareholders, our results can provide them with investment advice. They can invest in fintechs or traditional banks that meet regulatory requirements, have developed trends in risk management and performance, and are supported by local governments. Moreover, our models could help them estimate the future performance of the fintech or traditional bank of interest to test whether it is worth investing in. For the governments and policymakers, our results could provide a better understanding of how risks influence banks'/fintechs' performance. This could help them to develop more targeted policies and support provisions.

7.4 Limitations and future work

There are some limitations in this study that should be viewed as opportunities for future work. Firstly, the absence of any established research testing the different types of risks on fintechs in their performance, even though many studies investigated this area, limits studies on fintechs. As a new type of bank, our sample with a total of 33 fintechs was too small to provide generalised results for the whole industry. Thus, a larger sample of fintechs would have been better for statistical analysis. However, as the fintechs are newly established companies in the banking industry, there were only limited sample variables to be used in this research. Thus, as time passes, there should be more for future researchers to analyse. Nevertheless, the shortfall was overcome by analysing case studies, the qualitative results that enriched the research and the quantitative results gathered from the panel data regression models.

As we stated in Chapter 5, we were unable to obtain data on failure cases for analysis. The main reason for this is that all fintechs operate online. When a fintech company closes its operations, its data will disappear from the internet. Therefore, we do not have access to data on any closed fintechs. In addition, poorly run fintechs may delay publishing or may not publish financial and risk performance reports. Therefore, we could only select those 'successful' fintechs and collect data from their published annual or interim reports. Although only 'successful' fintechs are used, the cases we have selected can still help us understand how fintechs operate in risk management. Based on our analysis, we find some fintechs performed better than others during the investigated period and are considered worthy of investment that have the following conditions: 1. have released their annual or interim reports regularly; 2. meet regulatory requirements; 3. have developed trends in risk management and performance; 4. are supported by local governments.

Secondly, we could not capture all of the variables in risk management. As indicated in Chapter 3, this research used typical risk variables to test bank performance. However, as shown in previous studies, it can only focus on one or more of the risk variables to test their impacts, which still contributes to the literature. In addition, there were limited studies focused on fintechs. In this regard, future research could include more risk management variables.

Finally, we built several regression models to reach our results. Future researchers could summarise a whole regression model with dummy variables, such as using dummy variables for bank types and countries when they have enough large sample size to represent the industry. Also, this research was collected only from banks and fintechs in China, the UK and Australia. In order to achieve more generalised results, other countries could be added. While the limitations of this research are acknowledged, the achieved results are not reduced in their significance and contributions.

7.5 Overall conclusion

We have shown the importance of risk management in banks' performance in both traditional banks and the newly established fintechs. With the behaviour change of consumers in receiving financial products and services, fintechs have taken on a more important role in the banking industry. Thus, managers in traditional banks and fintechs need to pay attention to risk management to achieve better performance. We aimed to analyse the differences and similarities existing between the two types of banks. Moreover, in order to achieve more comprehensive results, we analysed this topic in three countries (China, the UK and Australia). After reviewing the previous literature, we built a methodology with quantitative and qualitative approaches to obtain our results. Based on analysing these results, we provided discussions and suggestions. Thus, we showed new insight into bank risk management which could be the foundation for future studies and working models for managers, investors and policymakers.

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APPENDICES

Appendix 1 Dummy variable analysis (Random-effects estimates)

Through our literature review in the traditional banking industry, we noted that when investigating banks in China, researchers often add a dummy variable to determine the effects of bank ownership regarding whether the bank is a state-owned bank or a joint-stock commercial banks or an other types of commercial bank on bank performance. For example, Fu & Heffernan (2009) and Tan (2016) both use dummy variables to represent the ownership of the Chinese traditional banks and test its influence on bank performance. Thus, in order to have a comprehensive result for Chinese traditional banks, we also add a dummy variable to indicate bank ownership to compare their performance to other traditional banks. The dummy variable is equal to one for state-owned banks (SOB) and zero for other traditional banks.

As noted in our methodology, the standard form of the panel data regression model is $y_{it} = \beta_0 + \sum_{j=1}^{k} \beta_j x_{jit} + u_{it}$, where y represent the dependent variables; x represents the independent variables; β_0 represents the constant term; $\beta_j\,(j = 1, \dots, k)$ are coefficients to be estimated; i and t are indices for the sections and time, respectively; $u_{it} = \alpha_i + \varepsilon_{it}$, where α_i is the individual-specific unobserved effect. For the random-effects approach, the individual-specific unobserved effect includes unobserved time-invariant and group-specific effect. ε_{it} is the error term. Following a similar approach, we also run random-effects models with the addition of a dummy variable. The form of the model becomes $y_{it} = \beta_0 + \sum_{j=1}^{k} \beta_j x_{jit} + \gamma SOB_i + u_{it}$, where y represent the dependent variables; x represents the independent variables; β_0 represents the constant term; $\beta_j\,(j = 1, \dots, k)$ and γ are coefficients to be estimated for the dummy variable; i and t are indices for the sections and time, respectively; $u_{it} = \alpha_i + \varepsilon_{it}$, where α_i is the individual-specific unobserved effect and ε_{it} is the error term.

With the dummy variable in the dataset, the F test, LM test and DWH test results were not changed. Random-effects models were still suitable and were applied in all panel data regression models for Chinese traditional banks. The estimates of the panel data regression models are constructed in Table A1.1 and include three models based on three dependent variables.

	ROA		ROE		EPS	
	Estimates	R.S.E	Estimates	R.S.E	Estimates	R.S.E
Intercept	0.0378	0.0634	0.1903	0.6057	0.0357	0.5720
NPL	-0.1426**	0.0680	-2.2775**	1.1412	-0.8983*	0.6145
NCO	-0.0104	0.0255	-0.0043*	0.4288	-0.1632*	0.2260
LoanR	-0.0199*	0.0323	-0.0785	0.5365	-0.0252	0.2902
VaR	-0.0001**	0.000022	-0.0006*	0.00037	-0.0006***	0.0002
LCR	0.0005*	0.0017	0.0032*	0.0286	0.0094*	0.0150
CR	0.0335	0.0601	0.3338**	0.5562	0.7064*	0.5396
T1	0.0025**	0.0321	0.2331***	0.5368	0.3351	0.2887
D/A	-0.0040	0.0112	-0.1796**	0.1823	-0.0171*	0.1034
D/E	-0.0004**	0.0007	-0.0076***	0.0116	-0.0006	0.0063
BVC %	0.0029***	0.0035	0.0444	0.0590	0.011**	0.0304
ORP %	-0.0003*	0.0137	-0.0459*	0.2152	-0.1006*	0.1303
Ln(Asset)	-0.0022***	0.0007	-0.0243**	0.0107	-0.0085***	0.0075
C/I	-0.0110**	0.0068	-0.2128**	0.1162	-0.0366***	0.0608
SOB	0.0072**	0.0020	0.0737**	0.0294	0.0191	0.0219
R^2_{within}	0.5062		0.3918		0.3346	
$R^2_{between}$	0.5769		0.4537		0.4062	
$R^2_{overall}$	0.3053		0.2688		0.2384	
No.	110		110		110	

Table A1.1 Random-effects estimation results for China (with the SOB dummy variable)

Note: *, **, *** represent significance at the 10%, 5% and 1% levels respectively.
R.S.E represent robust standard error.

For all dependent variables (ROA, ROE and EPS), the results are consistent with the results found in Section 4.2. For example, all credit risk variables have a negative influence. This suggests that higher credit risks would lead to worse performance. In more detail, NPL is significant for all three variables (ROA, ROE and EPS) at 5%, 5% and 10%, respectively. This suggests that NPL is significantly important in credit risk management for Chinese traditional banks. Moreover, LoanR estimates shows 10% significance for ROA and NCO estimation shows 10% for ROE and EPS. This suggests that besides NPL, managers should also pay attention to these variables when managing credit risks. Moreover, NPL shows the highest coefficient value in three credit risk variables for all three dependent variables. This further shows the importance of NPL in credit risk management. The market risk variable, VaR, also has a significant negative effect on all three dependent variables. With its significance, VaR should be considered during risk management. However, as estimate values are relatively small, combined with a relatively stable financial situation in China, traditional banks can worry less about the impact of market risk.

With regards to the capital and liquidity risk variables, LCR, CR and T1 have positive impacts on bank performance. This suggests that increased tier one capital and liquidity holding percentages in the traditional banks would improve their asset performance. In more detail, LCR shows its positive influence for all three variables at the 10% significance level and T1 shows the 5% and 1% significance level for ROA and ROE, respectively. This indicates that Chinese traditional banks should follow legal requirements and increase liquidity and capital levels while managing liquidity and capital risks. Moreover, CR shows its significance at the 5% and 10% level for ROE and EPS, respectively. CR also shows highest coefficient values in three variables. This suggests that besides achieving the legal requirements, managers should consider CR when managing liquidity and capital risks. With respects to debt level variables, both D/A and D/E have negative impacts on bank performance. In more detail, D/A is significant for ROE and EPS at the 5% and 10% significance level respectively, and D/E is significant for ROA and ROE at the 5% and 1% significance level respectively. Moreover, D/A shows higher coefficient value than D/E for all three dependent vairbales. Thus, managers should control and reduce the debt level and focus more on D/A, which could increase bank performance during risk management.

For the selected operational risk variables, both ORP and C/I show significant negative influences on bank performance. This result proves the importance of operational risks and managers should take extra care when managing operational risks. Reducing operational issues and their costs could help Chinese traditional banks developing their bank performance. With regards to reputational risks, BVC shows positive impacts on all three dependent variables and shows its significance at the 1% and 5% for ROA and EPS, respectively. This suggests that managers should increasing traditional banks' reputation during operations which could help banks to receive better performance. Moreover, ln(asset) has a significant negative impact at bank performance with the 1% level for ROA and EPS and at the 5% level for ROE. This means that a higher asset level will reduce bank performance. The highly significant level indicates the strong influence of ln(asset) on bank performance. Thus, the result suggests that maintaining or decreasing the acceptable amount of assets could help traditional banks perform better. This result confirms findings from previous studies (e.g., Geng, 2016, Tan, 2016 and Zhang, 2010) that also showed a negative relationship between ln(asset) and bank performance.

In addition, the dummy variable (state-owned banks) also shows a consistent result for three dependent variables. SOB presents a positive impact on bank performance, which suggests that state-owned banks enjoyed more scale efficiency than other banks. Moreover, SOB is only significant in the models of ROA and ROE, which indicates that the ownership of bank influences its performance in assets and equity but does not significantly affect bank performance in the share market. This result is in line with Tan (2016) for Chinese traditional banks. He/She showed a positive relationship between SOBs and bank performance. However, the result is the opposite of that found by Fu & Heffernan (2009), who argued that SOBs have lower bank performance. Our finding could be explained as, with the advantages of larger business scale and variety, SOBs could reduce their costs and thereby increase bank performance.

Similarly, besides interpreting variables, we looked at the R^2 for our random-effects models. R^2(within) shows a 51% variation for ROA, 39% for ROE and 33% foe EPS within one traditional banks over time. R^2(between) shows 58% variation for ROA, 45% for ROE and 41% foe EPS between traditional banks. R^2(overall) shows 31% for ROA, 27% for ROE and 24% foe EPS for traditional banks. This shows that Chinese traditional banks have higher variation with regards to ROA.

In summary, in order to have a comprehensive result for Chinese traditional banks, we added a dummy variable to test if the ownership of banks influences bank performance. Our overall conclusion is consistent with obtained showed in Chapter 4.2. With adding the dummy variable, the results further show that if the bank is a state-owned bank, the performance will be better than other banks in China. In addition, as noted in Chapter 3, the reason for not adding the dummy variable to traditional banks in the UK and Australia is that there are no state-owned banks in these countries. Thus, this research only adds the dummy variable for Chinese traditional banks as shown here in Appendix 1, not in our analysis in Chapter 4.

Appendix 2 Dummy variable analysis (GMM estimates)

As noted in Chapter 3 and Appendix 1, this section applies GMM for Chinese traditional banks by adding the dummy variable, state-owned banks (SOB). For all dependent variables (ROA, ROE and EPS), the estimates are consistent with the results obtained in GMM for Chinses traditional banks in Chapter 4. Therefore, reducing credit risks, market risks, debt level and operational risks could help banks to improve their performance. At the same time, improving liquidity and capital holding level and reputation could also help banks improve their bank performance. In addition, Chinese traditional banks should keep their size stable and reduce unnecessary assets to achieve better performance.

Concerning the SOB in our GMM estimations, instead of all significant positive impact on the performance shown in random-effects panel data regression models, the GMM estimates show different results. The SOB only has a significant positive influence on the ROA, and has a negative impact on the ROE. These results show that state-owned banks enjoyed more scale efficiency than other banks in ROA and EPS. This suggests that the SOB has a better ROA performance with a significant positive influence on ROA than other traditional banks in China. Moreover, based on the DWH tests, we confirmed there is no endogeneity problem in our dataset. The difference here suggests that SOBs should keep their operations smooth. Although they could not enjoy the scale efficiency for ROE, SOBs could enjoy the scale efficiency for ROA and EPS. Additionally, as the coefficient value is not significant on ROE and EPS, based on the significant result for ROA, this finding is consistent with Tan (2016) and inconsistent with Fu & Heffernan (2009). The possible reason could be that with the advantages of larger business scale and variety, SOBs can reduce their costs and increase ROA performance.

As noted in Chapter 3, in order to have a comprehensive result for Chinese traditional banks, we add a dummy variable to test if the ownership of a bank influences bank performance. Our overall conclusion is consistent with the findings shown in Chapter

4.2 and Appendix 1. In summary, besides the dummy variable, the result stays consistent for risk variables. Reducing credit risks, market risks, debt level risks and operational risks could increase bank performance. While increasing liquidity and capital holing levels and brand value could increase bank performance. Moreover, cutting unnecessary assets could also help Chinese traditional bank increase their performance. The estimate of the dummy variable suggests that if the bank is state-owned, then ROA performance will be better than other banks in China. Moreover, as said before, not adding the dummy variable to traditional banks in the UK and Australia is that there are no state-owned banks in these countries. Thus, this research only adds the dummy variable for Chinese traditional banks and shown here in Appendix 2.

	Estimations		
	ROA	ROE	EPS
Intercept	0.1300	0.3673	-0.4587
One period lag of dependent variable	0.3465*	0.4889***	0.0481
Non-performing loan ratio	-0.0538*	-0.1490***	-0.7114*
Net Charge-off rate	-0.0084	-0.3215*	-0.2716*
Total loan loss ratio	-0.0009*	-0.1521	-0.3391*
Value at risk	-0.0001	-0.0004**	-0.0010***
Liquidity coverage ratio	0.0010*	0.0282*	0.0030
Current ratio	0.0597	0.2685	0.4926*
Tier 1 capital ratio	0.0069**	0.7651*	0.0515*
Debt-to Asset ratio	-0.0199	-0.4006*	-0.0931*
Debt-to-Equity ratio	-0.0013*	-0.0271	-0.0037
Brand value change %	0.0008***	0.0025	0.0177*
Operational risk %	-0.0031*	-0.1036*	-0.0870*
Ln(Asset)	-0.0048*	-0.0544**	-0.0034*
Cost-to-Income ratio	-0.0117	-0.1497	-0.0955*
State-owned banks	0.0016**	-0.0152	0.0030
F-test	169.3***	184.8***	201.0***
Sargan Test (p-value > χ^2)	49.7(0.565)	60.5(0.196)	42.6(0.821)
AR(1)	z = -5.84 p-value = 0.00	z = - 3.71 p-value = 0.00	z = -2.04 p-value = 0.00
AR(2)	z = -0.39 p-value = 0.70	z = -0.99 p-value = 0.32	z = -0.08 p-value = 0.94
Obs.	110	110	110

Table A2.1 GMM estimation results for China (with the SOB dummy variable)

Notes: *, **, *** represent significant at 10%, 5% and 1% respectively.

Sargan test is the test for over-identifying restrictions in GMM dynamic model estimation.

AR(1) and AR(2) are Arellano-Bond test that average autocovariance in residuals of order 1 and 2 is 0 (H_0: no autocorrelation).

Appendix 3 Random-effects estimates without outliers for Australian fintechs

As we observed in Chapter 4, some outliers exist in fintechs for all three countries. However, there are not enough observations to test Chinese and UK fintech's EPS with deleting the outliers. Thus, we should give fintechs a longer time to have more fintechs join the share market, and then we will have enough data to analyse. Thus, in order to check the influence of these outliers to get more comprehensive results, we rerun the random-effects estimates for Australian fintechs without outliers.

Firstly, we rerun White's test to see if heteroscedasticity still exists. Results of White's test in Table A3.1 shows that heteroscedasticity was still present in data without outliers. Since heteroscedasticity causes standard errors to be biased, after finding the proper static panel model, we used robust standard errors.

Fintechs	ROA model	ROE model	EPS model
White's test (p-values)	0.0001	0.0000	0.0000

Table A3.1 Tests for heteroscedasticity

Next, we rerun the F, LM and DWH tests after deleting the outliers of the Australian fintechs' dataset. The results are consistent with the results showed in Chapter 4. Random-effects models were still suitable and were applied in all panel data regression models for Australian fintechs. Table A3.2 shows tests for determining the most appropriate approach for Australian fintechs without outliers. The estimates of random-effects are constructed in Table A3.3 and include three models based on three dependent variables.

Test	p-values (ROA)	p-values (ROE)	p-values (EPS)
F	0.0000	0.0000	0.0000
LM	0.0000	0.0000	0.0000
DWH	0.3804	0.4660	0.5908

Table A3.2 Tests for determination the most appropriate approach for Australian fintechs without outliers

	ROA		ROE		EPS	
	Estimates	R.S.E	Estimates	R.S.E	Estimates	R.S.E
Intercept	-0.7333***	0.2121	-0.7515**	0.4583	0.0237	0.0763
NPL	-1.1843*	0.6338	-0.9681*	1.2075	-2.6271*	1.9913
NCO	-2.1031	0.6829	-3.6701*	1.4634	-2.0469	2.0003
LoanR	-1.0431*	0.6184	-2.2432*	1.1366	-0.9832*	1.9333
VaR	-0.0061*	0.0113	0.0159	0.0321	-0.0054*	0.0042
LCR	0.0279*	0.0670	0.0359*	0.2041	0.0157**	0.0212
CR	0.0212*	0.0215	0.0306	0.0748	0.2076	0.0084
T1	0.2246***	0.7462	0.4668***	1.6627	0.1215*	0.2313
D/A	-0.4501*	0.2167	-1.6009*	0.4604	-0.0284	0.0561
D/E	-0.0054	0.0033	-0.0237*	0.0074	-0.0041	0.0009
BVC %	0.0220*	0.0274	0.1093**	0.0972	0.0038*	0.0081
ORP %	-0.0078	0.0790	-0.2696**	0.1776	-0.2297**	0.1850
Ln(Asset)	0.0685**	0.0334	0.0118*	0.0742	0.0152**	0.0125
C/I	-0.0058**	0.0565	-0.0215**	0.0550	-0.0038	0.0199
R^2_{within}	0.6147		0.5489		0.5763	
$R^2_{between}$	0.6572		0.6026		0.6276	
$R^2_{overall}$	0.3403		0.3223		0.3712	
No.	74		74		65	

Table A3.3Random-effects estimation results for Australian fintechs (without outliers)

Note: *, **, *** represent significance at the 10%, 5% and 1% levels respectively.

R.S.E represent robust standard error.

1. Outliers included in the following fintechs at the time period: 'ChangeFinance' in 30/06/2015, 31/12/2015 and 31/12/2016; 'NovatiiGroup' in 31/12/2015 and 31/12/2016; 'Ondeck' in 31/12/2015 and 'WISR' in 31/12/2017.

For all dependent variables (ROA, ROE and EPS), the results are consistent with those in Section 4.5, except for the effect of D/E on EPS. For example, all credit risk variables have a negative influence. This suggests that higher credit risks would lead to worse performance. In more detail, NPL and LoanR are significant for all three variables (ROA, ROE and EPS) at the 10% significance level. NCO estimate shows its significance at the 10% level for ROE and the highest coefficient value in three credit risk variables for all three dependent variables. As credit variables showed similar significance level in above three regression models, it suggests that managers should consider credit variables with coefficient values more. All coefficient values of credit risk variables are smaller than were seen in the estimates from the model performed from the dataset containing outliers. This suggests that outliers increase the impact of credit risk variables on predicted bank performance but do not affect the overall findings.

Similar to results with the outliers, the market risk variable, VaR, has a significant negative impact on ROA and EPS at the 10% significance level but has a positive impact on the ROE. This further illustrates the complexity of market risk, and Australian fintechs should pay extra attention to market risk management. Managers should balance VaR values to achieve better overall performance.

With regards to the capital and liquidity risk variables, LCR, CR and T1 have positive impacts on bank performance. This suggests that increased tier one capital and liquidity holding percentages in the traditional banks would improve their asset performance. In more detail, LCR shows its significance positive influence for all three variables at the 10%, 10% and 5% significance level, respectively. CR shows its significance at the 10% level for ROE, while T1 shows its significance at the 1%, 1% and 10% significance level for ROA,ROE and EPS, respectively. Moreover, T1 also shows highest coefficient values in three regression models. This indicates that Australian fintechs should follow legal requirements and increase liquidity and capital levels while managing liquidity and capital risks. Managers should consider T1 more based on its higher significance level and coefficient values.

With respects to debt level variables, different results are shown. Both D/A and D/E have a negative impact on bank performance. This suggests that the outliers influence the D/E's impact on the EPS. However, the change of influence of D/E does not impact our suggestions as we found the negative impact of D/E on the EPS in our GMM estimates with outliers. Our results provide further evidence of the importance of running random-effects and GMM estimates simultaneously to test the dataset. In more detail, D/A is significant for ROA and ROE at the 10% significance level, and D/E is significant for ROE at the 10% significance level. D/A shows higher coefficient values than D/E for all three dependent variables. Thus, our suggestions are the same. Managers should control and reduce the debt level and focus more on D/A, which will improve the fintechs' performance in the risk management process.

For the selected operational risk variables, both ORP and C/I show negative influences on bank performance. The importance of ORP in operational risk management increased when outliers were removed. In the random-effects estimates for Australian fintechs without outliers, ORP increased the coefficient values for all three variables and showed higher significance levels and coefficient values than C/I. This suggests that reducing operational issues and their costs could help Australian fintechs to their performance.

Similar to the results with outliers, the reputational risk variable BVC shows a positive impacts on all three dependent variables. Moreover, BVC shows its significance at the 10%, 5% and 10% level for ROA, ROE and EPS, respectively. This suggests that managers should increase fintechs' reputation during operations which could help banks to attain better performance. With regards to the bank size, ln(asset) has a significant positive impact on bank performance at the 10% level for ROE and at the 5% level for ROA and EPS. This means that a higher asset level will increase bank performance. This is also consistent with results with outliers included and confirms our findings that increasing their size could help fintechs improve their performance.

Similarly, besides interpreting variables, we looked at the R^2 for our random-effects models. R^2(within) shows a 61% variation for ROA, 55% for ROE and 58% for EPS within fintechs over time. R^2(between) shows 66% variation for ROA, 60% for ROE and 63% foe EPS between fintechs. R^2(overall) shows 34% for ROA, 32% for ROE and 37% foe EPS for fintechs. This shows that Australian fintechs have higher variation with regards to ROA.

In summary, we found random-effects estimates without outliers for Australian fintechs. The overall findings are consistent compared with the analysis in Section 4.5, except for the D/E in EPS. Even without outliers, fintechs still need to improve bank risk management to help them achieve successful performance. Furthermore, as outliers are part of the performance of these fintechs, we cannot simply remove them and then analyse the rest of the data. Therefore, the analysis without outliers is presented here in Appendix 3 rather than in Chapter 4.

Appendix 4 GMM estimates without outliers for Australian fintechs

Similar to Chapter 4, we also rerun the GMM estimates for Australian fintechs without outliers. The estimates from the GMM are constructed in Table A4.1 and include three models based on three dependent variables.

	Estimations		
	ROA	ROE	EPS
Intercept	-01.491***	-3.2195***	0.2254
One period lag of dependent variable	0.0505	0.2458*	0.0518**
Non-performing loan ratio	-3.7734*	-1.3353*	-1.1664***
Net Charge-off rate	-6.6597*	-9.9603*	-1.2782***
Total loan loss ratio	-4.6012*	-5.7208**	-1.5498***
Value at risk	-0.0054	-0.0224*	-0.0061**
Liquidity coverage ratio	0.0283*	0.0936*	0.0053*
Current ratio	0.0099	0.0044	0.0027
Tier 1 capital ratio	0.9913***	0.1830*	0.0726*
Debt-to Asset ratio	-0.8122***	-0.0854	-0.0815***
Debt-to-Equity ratio	-0.0311***	-0.0170*	-0.0017*
Brand value change %	0.0927***	0.0391*	0.0052*
Operational risk %	-0.2469	-0.1784**	-0.2934***
Ln(Asset)	0.0301*	0.0122**	0.0002*
Cost-to-Income ratio	-0.0228**	-0.0943*	-0.0209***
F-test	292.7***	201.2***	279.1***
Sargan Test (p-value > χ^2)	33.04(0.511)	31.2(0.583)	23.0(0.993)
AR(1)	z = -3.01 p-value = 0.00	z = -3.45 p-value = 0.00	z =-3.34 p-value = 0.00
AR(2)	z = -0.84 p-value = 0.41	z = -0.40 p-value = 0.68	z = -0.29 p-value = 0.78
Obs.1	74	74	65

Table A4.1 GMM estimation results for Australian fintechs (without outliers)

Notes: *, **, *** represent significant at 10%, 5% and 1% respectively.

Sargan test is the test for over-identifying restrictions in GMM dynamic model estimation.

AR(1) and AR(2) are Arellano-Bond test that average autocovariance in residuals of order 1 and 2 is 0 (H_0: no autocorrelation).

1. Outliers included in the following fintechs at the time period: 'ChangeFinance' in 30/06/2015, 31/12/2015 and 31/12/2016; 'NovatiiGroup' in 31/12/2015 and 31/12/2016; 'Ondeck' in 31/12/2015 and 'WISR' in 31/12/2017.

Firstly, the F-statistics confirm the significance of the variables. The Sargan test shows the there is no evidence of over-identifying restrictions. The AR tests show that the estimates of the parameters of the independent variables are consistent for our GMM. Moreover, the significant coefficients of the lagged performance variables (ROE and EPS) confirm the dynamic character of the model specification. For Australian fintechs, the significant coefficients of the lagged performance variables confirm the dynamic character of the model specification. These results suggest that the performance of Australian fintechs seems to persist and implies that the Australian fintechs are in a competitive market structure.

For all the dependent variables (ROA, ROE and EPS), the results are consistent with the results found in Section 4.5. For example, all credit risk variables have a significant negative influence on bank performance. This suggests that higher credit risk would lead to worse performance. Similar to the random-effects model in Appendix 3, the NCO estimate shows the highest coefficient value of the three credit risk variables for all three dependent variables. This suggests that managers should consider credit variables with significance levels along with coefficient values. Moreover, all coefficient values for credit risk variables are smaller than they were for the estimates with the outliers. This suggests that outliers increase the impact of credit risk variables on bank performance but do not affect the overall findings.

Similar to results with the outliers, the market risk variable, VaR, has a significant negative impact on all dependent variables. Similar to the results with outliers, there is no endogeneity problem in our dataset as we tested. Moreover, the VaR is significant in the GMM model but not in the random-effects model. The results shown here suggests that Australian fintechs should be concerned more with market risks. Furthermore, as the results for the other two dependent variables are consistent, Australian fintechs should keep VaR at a reasonable level and reduce the risk, if possible, to achieve better performance.

With regards to the capital and liquidity risk variables, LCR, CR and T1 have positive impacts on bank performance. This suggests that increased tier one capital and liquidity holding percentages in the traditional banks would improve their asset performance. In more detail, LCR shows its significant positive influence for all three variables at the 10% significance level, while T1 has its significance at the 1%, 10% and 10% significance level for ROA, ROE and EPS, respectively. Moreover, T1 also shows the highest coefficient value of the three variables. This indicates that Australian fintechs should follow legal requirements and increase their liquidity and capital levels while managing liquidity and capital risks. Managers should consider T1 more based on its high significance level and coefficient values. With respect to debt level variables, consistent results are shown. Both D/A and D/E have a negative impact on bank performance. In more detail, D/A is significant for ROA and EPS at the 1% significance level, and D/E is significant for ROA at the 1% significance level and ROE and EPS at the 10% significance level. D/A shows a higher coefficient value than D/E for all three dependent variables. Thus, in order to achieve better performance, managers should control and reduce debt levels.

For the selected operational risk variables, both ORP and C/I show negative influences on bank performance. Similar to Appendix 3, the importance of ORP in operational risk management increased when outliers were removed. ORP increased its coefficient values for all three variables and showed higher significance levels and coefficient values than C/I. This suggests that reducing operational issues and their costs could help Australian fintechs to develop their performance.

Similar to the results with outliers, the reputational risk variable BVC shows a significant positive impact on all three dependent variables. This suggests that managers should increase fintechs' reputation during operations which could help banks to achieve better performance. With regards to bank size, ln(asset) also shows a significant positive impact on all three dependent variables. This means that a higher asset level will increase fintechs' performance. This is also consistent with our results with outliers and comfirms our findings that increasing size could help fintechs to improve their performance.

In summary, we applied random-effects estimates without outliers to Australian fintechs. The overall findings are consistent with our analysis in Section 4.5. Even without outliers, fintechs still need to improve bank risk management to help them achieve successful performance. Furthermore, as outliers are part of the performance of these fintechs, we cannot simply remove them and then analyse the rest of the data. Therefore, the analysis without outliers is presented here in Appendix 3 rather than in Chapter 4.