UNIVERSITY OF SOUTHAMPTON

FACULTY OF SOCIAL SCIENCE

SOUTHAMPTON BUSINESS SCHOOL

THREE ESSAYS ON THE DYNAMICS OF EARNINGS MANAGEMENT

by

XIAO ZHANG

Supervisor: Dr. Surendranath Rakesh Jory

Supervisor: Professor Tapas Mishra

Internal Examiner: Dr. Alaa Zalata

External Examiner: Dr. Abdelhafid Benamraoui

Thesis for the degree of Doctor of Philosophy

August 2020

UNIVERSITY OF SOUTHAMPTON

Abstract

FACULTY OF SOCIAL SCIENCES

SOUTHAMPTON BUSINESS SCHOOL

Doctor of Philosophy

by Xiao Zhang (Joyce)

This dissertation investigates financial and non-financial firms' earnings management (EM) practices. It aims to shed light on firms' EM practices by emphasising the consequences and incentives of EM. The dissertation is based on three complementary studies.

The first study focuses on the EM activities of non-financial firms. We propose a mechanism to estimate a relatively noise-free impact of earnings management on firms' subsequent stock performance. Taking the United States as our empirical context and covering two decades of data (1990-2016), we find a negative association between firms' subsequent stock performance and aggressive earnings management. Our findings further suggest that investors react differently towards different approaches of earnings management, therefore, price correction occurs at different future periods for earnings manipulators. Additionally, when examining the effectiveness of the impacts, we find that investors and regulators who use accrual-based earning management (AEM) and real activities earnings management (REM) indicators individually to detect firms' earnings management behaviour can be misled. Therefore, we propose an approach that combines AEM and REM, respectively, with the M-Scores to better capture aggressive earnings manipulators. This study has implications for investors and regulators with regards to detecting and eliminating firms' artificial earnings management activities.

The second study focuses on the EM practices of commercial banks whereupon we generate a new indicator based on EM named accounting managerial behaviour (AMB). The study examines whether accounting managerial behaviour is associated with future bank performance. In this paper, accounting managerial behaviour is defined as the interaction of earnings management and bank efficiency (or managerial ability) matrix. Based on a sample of 589 commercial banks from the United States (U.S.) over a period of two decades (1998-2017), we show that banks with superior accounting managerial behaviour outperform their peers, whilst banks with poor accounting managerial behaviour underperform their peers in the near future. Our evidence suggests that banks short-term decisions, resource utilization and internal attributes could affect their long-term performance. We further find that the size effect on future bank performance can be dominated by banks' accounting managerial behaviour, highlighting the importance of accounting managerial behaviour in commercial banking studies.

The third study is an event-based EM research. This study investigates the impact of TARP on commercial banks and bank holding companies' earnings management practices, pure bank efficiency and manager-driven bank efficiency. Based on a sample of 598 banks across the period 2005 to 2013, we show that TARP did not affect banks' earnings management behaviour, neither their pure bank efficiency nor manager-driven bank efficiency in the long term. Further, we find that commercial banks and bank holding companies that received a larger amount of TARP funds had better bank efficiency following capital infusions. Our evidence also suggests that the TARP amount mainly affected recipients' pure efficiency, not the one driven by the ability of managers. Our evidence from this study suggests that TARP rescued banks from distress but did not fundamentally change the performance of its recipients compared to their counterparts, which implies that TARP is an effective temporary rescue project.

Overall, this dissertation contributes methodologically to EM detection literature, and contributes empirically to the literature of EM incentives and consequences.

Contents

List of Tables

List of Figures

Declaration of Authorship

I, Xiao Zhang declare that this thesis titled, 'Three Essays on the Dynamics of Earnings Management' and the work presented in it is entirely my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University;
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institutions, this has been clearly stated;
- Where I have consulted the published work of others, this is always clearly attributed;
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
- I have acknowledged all main sources of help;
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
- None of this work has been published before submission.

Signed: ....

Date: ....

Acknowledgements

I would like to express my sincere gratitude to a number of people, without whom I would not have been able to complete this thesis.

First of all, I would like to express my gratitude and appreciation to both of my supervisors, Dr Surendranath Rakesh Jory and Professor Tapas Mishra for their time and dedication spent in assisting me. Their guidance and assistance have been a real treasure towards my research. I greatly appreciate my main supervisor Dr Surendranath Rakesh Jory, for whom I have the highest respect. At the beginning of my journey, he was tremendously supportive. With his professional guidance, I was highly motivated and was able to progress my research at a significantly fast path. From this stage, I developed my basic research skills and learned how to work hard. At the later stage of my study, he provided freedom to let me explore and develop my own research habits. At this stage, I was able to choose an effective learning method and enjoy the research more. I am grateful to all the fair and constructive feedback and guidance that he has provided. My special thanks go to my secondary supervisor Professor Tapas Mishra, who has always been very patient, positive, enthusiastic and supportive to my research, and always being around providing guidance and suggestions towards my study and life. His critical thinking style as an economist has also benefited my way of thinking. I am extremely glad to have you both as my supervisors.

I am very grateful to Professor Collins Ntim and Dr Alaa Zalata for their participation in my PGR progression review committee and insightful feedback. I would like to say a special thank you to Professor Collins Ntim, from whom I obtained the inspiration of how to differentiate a paper and I realized the importance of having an active mind. My sincere thanks go to Dr Alaa Zalata, who has been extremely friendly to me and very helpful to my research. I would also like to thank all academics that have generously provided opinions and suggestions to my thesis in academic conferences.

I gratefully acknowledge the University of Southampton for providing a three-year funding and a precious academic environment during my PhD journey. My sincere gratitude goes to the University staffs who were always supportive. In particular, to Dr Bruce Hearn, the director of the Ph.D. programme and Dr Vadim Grievich, the faculty director of the Graduate School. My sincere thanks to both of you for sharing potential opportunities towards conferences, seminars, workshops and jobs.

I would like to express my thanks to friends that I have made during my time in Southampton. My great thanks to He He, Yun Lu and Hua Jin with whom I shared the joys and pains of this project. They have been very supportive and have provided plenty of help towards my research and life. My sincere thanks go to my friends/officemates, Fotini, Nadirah, Rom, Takron, William and Zee. Thank you for generating a relaxing, friendly and supportive environment and for the infinite and joyful talks. My unfailing gratitude also goes to all my other friends who have greatly contributed to my learning and research process.

Finally, from the bottom of my heart, I would like to say a big thank you to my mum, Mrs Xiuhua Xie, my dad, Mr. Renzhong Zhang, my husband, Christopher Michael Dillon, and my mother and father in law, Jill, Richard and Michael for always being my emotional basis. Their unreserved love and support were and will always be the most valuable fortune in my life.

Chapter 1 Introduction

1.1 Background

During the last few decades, firm managers have been taking actions to manipulate earnings to achieve their earnings targets, which are affected by factors such as firms' previous-period earnings, peer earnings and their managers' earnings preferences. This behaviour is called earnings management (EM). It is an accounting fraud that regulators have tried to control and it is also a behaviour that has received a considerable amount of attention from academics. EM relevant topics have been increasingly popular since 1988, when the Journal of Accounting Research published at least three papers that refer to EM (see Dye, 1988; Mcnichols and Wilson, 1988 and DeAngelo, 2020). However, the term of earnings management was initialized far before 1988 and a few EM-related studies were conducted prior to 1988 (e.g. Healy, 1985; Moses, 1987). The popularity of the EM topics may due to the U.S. economic recession in early 1980s, causing researchers to pay additional attention to firms' behaviour.

In 1990s, more researchers were dedicated to EM studies and the majority of those studies focused on investigating U.S. firms. Research has been conducted to explore the reasoning behind firms engaging in EM practices. For instance, Pourciau (1993) finds empirical evidence supporting that firm executives artificially decrease earnings in the year of the turnover and manage to increase earnings in the following year to prove their superior abilities in management. Perry and Williams (1994) document that firms tend to artificially reduce earnings prior to management buyouts to provide firms and their managers additional benefits during the buyouts process. Burgstahler and Dichev (1997) find evidence supporting that firms engage in EM practices to avoid earnings decrease and losses. Degeorge, Patel and Zeckhauser (1999) further document that firms manipulate earnings upwards to achieve positive profits, sustain recent performance and meet market expectations. They also find that EM firms have a worse future performance than firms that are not suspected as EM manipulators. Guidry, Leone and Rock (1999) posit that managers manipulate earnings upwards to optimize their short-term bonuses, using a relatively robust analysis controls for a confounding association between firms' long-term performance and their stock-based compensation. Erickson and Wang (1999) find that, during the mergers and acquisitions process, acquiring firms tend to artificially increase earnings to stimulate their stock prices prior to a merger agreement, to potentially reduce the merger costs.

A few studies focus on exploring the consequences of EM and most of them are event-based studies, especially events in the equity market. For instance, Teoh, Ivo and Wong (1998) document that discretionary accruals in the initial public offering (IPO) year are negatively associated with firms' stock returns in the following three years. They also find that IPO issuers from the top quartile of EM underperform issuers from the bottom quartile by 20%. Teoh, Ivo and Wong (1998) find that EM in the year around the seasonal equity offering year has an negative impact on stock returns in the 48 months thereafter. Rangan (1998) also studies the EM practices of firms around their seasonal equity offerings and documents that EM only adversely affect firms' earnings in the subsequent year following the offering.

The incentives of EM are also studied in the 1990s. For instance, Becker, Defond, Jiambalvo and Subramanyam (1998) find that clients of higher quality auditors engage in less upwards EM activities than lower quality auditors' clients, suggesting that higher quality of audits is associated with lower accounting flexibility. The reason could be that high-quality auditors constrain firms' aggressive EM practices by supervising firms to provide high quality financial reports with less bad news hoardings. Pope, Peasnell and Young (1998) find evidence indicating that firms' incentives to manipulate earnings upwards are negatively associated with the proportion of their outside board members, suggesting the importance of supervision in reducing firms' accounting frauds. Beatty and Harris (1998) document that public banks are more likely to manipulate earnings than private banks, because public firms contain more information asymmetry. This finding implies that firms' information asymmetry level has a positive impact on firms' EM engagement.

Most importantly, EM detection models that are widely applied in recent EM studies were developed in the 1990s. The most frequently cited models are developed by Jones (1991) and Dechow, Kothari and Watts (1998). Jones (1991) initialized a model to capture accrual-based earnings management by detaching the discretionary portion from total accruals, naming it discretionary accruals (AEM). Manipulating earnings using AEM is very easy and straightforward, however, it is easily detectable. Consequently, firms also manipulate earnings via real business activities to avoid this issue. Dechow, Kothari and Watts (1998) developed models to disclose real activities earnings management (REM), where firms manipulate their earnings through daily business. These two measures are both applied in Chapter 2 to measure EM of non-financial firms. Additional information of AEM and REM including their differences and applications will be introduced in Chapter 2.

In the 21st century, studies further develop the reasons (e.g. Roychowdhury, 2006; Chen, Lin, Wang and Wu, 2010; and Blankley, Comprix and Hong, 2013), incentives (e.g. Jin, Kanagaretnam, Lobo and Mathieu, 2013; Chahine, Mansi and Mazboudi 2015; Biddle, Ma and Song, 2016; Li, Ma and Song, 2018) and consequences (e.g. Xie, 2001; Gong, Louis and Sun, 2008; Cohen and Zarowin, 2010 and Campa and Hajbaba, 2016) of EM. Additionally, EM studies of financial firms (e.g commercial banks and bank holding companies) are frequently studied (e.g. Lobo and Yang, 2001; Kanagaretnam, Lobo and

Mathieu, 2004; Kanagaretnam, Lim and Lobo, 2010; Cheng, Warfield and Ye, 2011; Cohen, Cornett, Marcus and Tehranian, 2014) and the sample range of EM studies started to be international in the 21st century. Researchers have also investigated firms' EM practices in Europe, Japan, China, India, Indonesia, etc. (see Burgstahler, Hail and Leuz, 2006; Liu and Lu, 2007; Sarkar, Sarkar and Sen, 2008; Guo, Huang, Zhang and Zhou, 2015) during this period. In the meanwhile, international comparisons of EM are frequently studied and the main interest of most studies lies in the association between EM and investor protection (see Leuz, Nanda and Wysocki, 2003; Chih, Shen and Kang, 2008; Enomoto, Kimura and Yamaguchi, 2015). Recent EM studies, especially studies during the past 15 years, are more updated and instructive to the following three papers (chapters) in this thesis. Therefore, the reviews of those studies will be further elaborated on in the following chapters, primarily from the background and literature reviews sections in chapter 2 to 4. For this reason, the recent EM studies are briefly summarized in this section.

1.2 Research Context

Accounting information plays a dual role of informativeness and stewardship (Bushman, Engel and Smith, 2006). Accounting information provides company owners, stakeholders, managers, creditors and other third parties reliable information of a firm's financial status, it also acts as a steward to summarize business healthiness in a given accounting period. Firm managers may acquire the accounting information to estimate the achievements of existing business and managerial decisions, then adjust their business plans accordingly. As a portion of the accounting information, earnings play an important role in financial analysis. Earnings are used along with firms' other financial attributes to reflect current business achievements as well as predicting companies' future cash flows and potential risks. Investors could use earnings together with other firm attributes to estimate the potential rate of returns of their investment and adjust their investment strategies to maximize their future profits. The benefits from attractive earnings in supporting future business lead to firms' EM intentions. Additionally, earnings management concerns the potential illegal and unethical transfer of wealth (Perry and Williams, 1994), while the wealth transferring could affect the benefits of investors and stakeholders and may increase the level of information asymmetry in the market. This study aims to investigate firms' EM activities to reverse the chain (i.e. eliminate EM practices) by assisting investors with detecting and correcting EM firms' fraudulent financial reports.

During the past 10 years, EM studies using U.S. sample firms are frequently studied. However, the majority of attentions are paid to the incentives of EM leaving the consequences of EM to be further investigated. For instance, female chief financial officers (CFOs) are found to be more conservative and manipulate earnings downwards compared with male CFOs (Peni and Vähämaa, 2010). Firms' are also found to engage in additional EM practices at the beginning of their chief executive officer (CEO) tenure (Ali and Zhang, 2015). We initiate this study to contribute to EM literature using updated samples and to further shed light on the importance of EM research especially from the EM consequences prospective. Furthermore, studying EM consequences could provide firm managers a better understanding towards the costs of their manipulative actions, which could also help mitigate managers' EM intentions. Less EM intentions would lead to a more transparent and efficient financial market. As a result, chapter 2 and chapter 3 in this thesis mainly focus on the consequences of EM in non-financial and financial firms. On the other hand, the study of EM incentives is increasingly popular during the past decade due to the existence of research gaps, which implies that EM incentives have not yet been fully investigated. Consequently, chapter 4 in this thesis will focus on investigating the EM incentives.

1.3 Structure of the Thesis

In general, there are two directions of earnings management, income-increasing (aggressive) earnings management and income-decreasing (conservative) earnings management. According to prior studies, firms conduct aggressive EM to avoid reporting negative and decreasing earnings, to meet or beat analysts' forecasts and peer performance, as well as to increase managers' benefits (see Roychowdhury 2006; Chen, Lin, Wang and Wu 2010; Blankley, Comprix and Hong 2013; Huang, Lao and McPhee 2017; Du and Shen 2018). In contrast, firms engage in conservative EM to reduce cost of capitals, boost stock prices, and to smooth high-level profits (see Kanagaretnam, Lobo and Mathieu 2004; El Sood 2012; Barth, Gomez-Biscarri, Kasznik and López-Espinosa 2017). In this study, we are more interested in firms' income-increasing EM practices because these activities have more profound impacts on the economy than firms' income-decreasing practices.

Not only do EM directions vary, EM approaches also differ. Firms take different actions to manipulate earnings in various industries. Non-financial firms manage earnings by artificially manipulating their accruals, cash flows from operations, production costs and discretionary expenses, whereas banks and bank holding companies use loan loss provisions and realised security gains and losses to manipulate earnings. In this study, our attention is paid to EM practices in both financial and non-financial industries, to provide a relatively comprehensive view of the association between EM and subsequent firm performance.

The majority of previous studies have investigated EM practices of non-financial firms. Those studies document that EM is positively associated with stock price crash risks, CEO turnovers and cost of capitals (Francis, Hasan and Li 2011; Hazarika, Karpoff, & Nahata, 2012; Kim & Sohn, 2013); and negatively affects firms' credit ratings, bond yield spreads (Ge & Kim, 2014) and future stock performance (Teoh and Wong, 2002; Chang, Chung & Lin, 2010; Cohen & Zarowin, 2010; Yang, Hsu, & Yang 2016; and Campa & Hajbaba, 2016). The impact of EM on firms' subsequent stock performance has been widely studied, however, the majority of these studies are conditional upon specific events, such as initial public offerings and secondary equity offerings. Only a few researchers have studied the unconditional impacts of EM on non-financial firms' subsequent stock returns. However, a better understanding of the unconditional impact of EM on stock performance can be an interest to firm managers as well as institutional and individual investors. Firm managers need the EM information to adjust and improve their business strategies in order to stimulate their firms' market value in the stock exchange, whilst investors need the understanding to assist with investment decisions in order to maximize their returns. Therefore, in chapter 2, we initiate the investigation of EM by providing a view of an unconditional association between EM and future stock performance.

Compared with previous research that also studies this unconditional association, we propose a mechanism to estimate a relatively noise-free unconditional impact of EM on firms' subsequent stock performance. We propose a new measure of EM that considers EM intentions to eliminate the misleading probabilities caused by traditional EM measures in singling non-financial firms' stock returns. Our new measure combines discretionary accruals-based earning management (AEM) and real activities earnings management (REM), respectively, with the M-Scores. Our results suggest that investors and regulators who use AEM and REM indicators individually to detect firms' earnings management behaviour can be misled. We document that the new measure we propose can better capture non-financial firms' aggressive EM practices. Overall, our findings from chapter 2 have implications to investors and regulators with regards to detecting firms' artificial earnings management activities in non-financial industries.

Then we move on to investigate financial firms' EM practices in Chapter 3. Among the financial firms, we focus on studying the EM behaviour of commercial banks, which plays a prominent role in the financial system and the economy. The majority of banks in the United Sates are not public listed banks; therefore, we study the impact of EM on future bank profitability and asset quality instead of banks' future stock returns. Studying an unconditional association between EM and bank performance is essential because it could be an interest to bank managers and depositors. Bank managers generally require more information to improve banks' profits and depositors could use the information to help evaluate the safety of their savings. A few studies have investigated the association between EM and subsequent bank performance, however, no agreement has been made on the sign of the association (see Wahlen 1994; Beaver and Engel 1996; Ahmed, Takeda and Thomas 1999; Cohen, Cornett and Marcus 2014). Consequently, we re-conduct the research using an updated sample of banks and we stabilize the signalling effect of EM on bank performance by introducing additional factors.

Using bank efficiency (BE) and managerial ability (MA) as additional factors together with EM, we are able to generate a new factor named accounting managerial behaviour (AMB). We document that banks with superior AMB, a combination of a low level of EM and a high level of BE (or MA), perform better than other banks in the next fiscal year. In contrast, we find that banks with poor AMB, a combination of a high level of EM and a low level of BE (or MA) underperform their peer banks in the following year. Our research offers strong evidence that banks' AMB is associated with their future performance. We also explore the size effect on the association among U.S. banks, and find that bank size has a positive impact on superior AMB banks' future performance, whereas the size of banks negatively affects poor AMB banks' future performance. Our findings suggest that AMB potentially dominates the size effect on bank performance. Overall, our findings from chapter 3 have implications to bank managers, stakeholders and investors by providing a signal towards future bank performance using AMB.

Then we move on to study the incentives of earnings management. The global financial crisis that was initiated in the United States spread worldwide from 2007 to 2009. During the global crisis, U.S. government had to provide support to both financial and non-financial institutions. Most funds are distributed to financial organizations, especially depositing institutions to guarantee the availability of credit, avoid bank run and increase the stability of the financial system. To avoid the bank run, U.S. government bailed out distressed banks using taxpayers' money. Therefore, taxpayers have the right to know the situation of banks preceding the financial crisis, and how well their money was used to improve the performance and behaviour of those distressed banks during the crisis. This leads us to investigate banks' attributes, particularly EM behaviour around the U.S. bailouts. Studying the EM practices around the financial crisis, especially towards the government intervention during the crisis can also assist regulators to acquire a better understanding towards banks' practices when they are distressed. A better understanding of banks' attributes during an economic recession could further help policy makers to design regulations more rationally when the economy faces similar circumstances in the future. Additionally, this understanding can assist not only U.S. policy makers, but also regulators in other countries as a paradigm, since the U.S. is one of the international financial centres. Therefore, we study the impact of a government intervention on banks' EM and several other attributes in Chapter 4.

Previous studies have found firms to engage in more income-increasing EM and less income-decreasing EM during the financial recession periods (Alali and Jaggi 2011; El Sood 2012). Whereas very few studies have investigated the association between government interventions and banks' EM decisions. Chapter 4 aims to fill this gap by exploring the impact of the Troubled Asset Relief Program (TARP) on banks' EM practices. Our results show that TARP does not affect banks' EM behaviour. We further find that TARP has no impacts on banks' pure (firm-specific) efficiency neither their manager-driven (manager-specific) bank efficiency in the long term. The pure efficiency is the efficiency driven by basic firm characteristics and the manager-specific bank efficiency is mainly driven by bank managers' characteristics. Our evidence also indicates that commercial banks and bank holding companies that received a larger amount of TARP funds have better pure bank efficiency following capital infusions. Overall, our evidence suggests that, from a view based on EM and bank efficiency, TARP rescued banks from distress but did not fundamentally change the performance of its recipients compared to their counterparts. This implies that TARP is an effective temporary rescue project, which means this project can be potentially duplicated to rescue distressed banks in the future when needed.

Overall, our research uses updated samples to shed light on firms' EM practices in various industries. This research further provides investors, regulators, policymakers and other market participators a better understanding of firms' earnings management behaviour and its signalling role towards firm performance. Our study also contributes to existing studies by exploring new approaches that could better capture firms' EM activities. We introduce several firm attributes to stabilize the signalling role of EM on future performance of financial and non-financial firms. In addition, this study contributes to the literature of EM incentives by investigating banks' EM practices around government bailouts.

The thesis is structured as follows. Chapter 2 empirically explores the impact of EM on non-financial firms' subsequent stock performance using EM measures that consider manipulative intentions. The results have implications for investors and regulators with regard to detecting non-financial firms' aggressive earnings management activities. Chapter 3 empirically studies the impact of EM on commercial banks' subsequent profitability and asset quality using efficiency-inclusive EM measures. The evidence highlights the importance of resource utilization in earnings management studies of the banking industry. Chapter 4 empirically examines the impact of TARP capital injections on banks' earnings management decisions and their efficiency. This chapter contributes to EM literature by stating that government interventions may have no impact on banks' EM practices in the long term. Chapter 5 concludes the thesis by highlighting the findings and contributions, reflecting on limitations and suggesting opportunities for future research.

Chapter 2 The Unconditional Risk-adjusted Investment-performance Measures of Stock Portfolios based on Earnings Management

2.1 Introduction

Earnings management (EM) is an approach that firms conduct to adjust financial statements in order to present an excessively positive view of their financial status. Aggressive EM[1] is a scandal that firms tend to hide from the public, and it is also a practice that regulators expect to control. A number of actions have been taken by the Securities and Exchange Commission (SEC) (e.g. the Sarbanes Oxley Act) to against firms that are suspected of EM. These actions inhibit firms from managing earnings by increasing market scrutiny. However, the actions have not entirely eliminated firms' EM practices and these practices are expected to affect investors, shareholders and firm managers. This study aims to investigate the consequences of firms' earnings manipulation behaviour with a main focus on the impact of EM on firms' future stock performance.

A common point of agreement in the literature is that the various strategies adopted by firms to manipulate earnings have signalling values. Gong, Louis and Sun (2008), Cohen and Zarowin (2010), Yang, Hsu and Yang (2016) and Campa and Hajbaba (2016), among others, show that the aggressive manipulation from both discretionary accruals (AEM) and real activities earnings management (REM) have adverse impacts on a firm's subsequent stock performance, under conditional circumstances such as seasoned equity offerings. Xie (2001) and Li (2010) document an adverse association between EM and firms' future stock performance without any conditional motives. However, the evidence from these two studies is driven from a sample of firms listed over 10 years ago on the United State (U.S.) stock exchanges. Due to the number of actions taken by SEC in the recent years, the consistency of the association between EM and future stock performance needs to be re-investigated.[2]

Additionally, previous studies mainly rely on AEM and REM to capture firms' EM practices, whereas AEM and REM may misidentify aggressive and conservative EM behaviour. According to the regulatory focus theory, when exposed to a decision-making process, individuals' preferred way to achieve goals are not necessarily fixed (Higgins, 1997). Using some EM approaches out of others makes it hard to detect firms' EM behaviour via the

[1] Manipulation could be aggressive (income-increasing) or conservative (income-decreasing). Aggressive (Conservative) ones are expected to negatively (positively) affect firms' future stock performance.

[2] For more information, please refer to the U.S. securities and exchange commission website: https://www.sec.gov/rules/final.shtml.

unused indicators. Therefore, using EM indicators individually to capture EM practices and predict firms' stock performance become controversial. This chapter aims to address this concern by exploring the EM misidentification phenomenon and structuring more effective EM indicators for signalling purposes.

Firms engage in aggressive AEM and REM activities to achieve short-term financial objectives, such as avoiding reporting negative earnings and meeting analysts' forecasts (Roychowdhury, 2006; Chen, Lin, Wang and Wu, 2010; and Blankley, Comprix and Hong, 2013). However, these objectives are negative signals to firms and could cost their subsequent share prices. Therefore, we expect aggressive EM to have an adverse impact on firms' future stock performance. Based on a sample of 9,859 firms listed on the major stock exchanges in the United States (US) from 1990 to 2016, we find evidence supporting that aggressive earnings manipulators underperform their peers subsequently. Our findings further suggest that diverse EM approaches impact future stock performance differently. We find that EM via discretional accruals and cash flow from operations mainly affects firms' subsequent 12-month stock returns but EM using production costs can influence returns for approximately 24 months.

Then, we design an approach to capture the misleading attributes of EM indicators. Our evidence confirms that AEM, REM and M-scores based approaches, individually, can mislead firms' EM detection, but a combination of these approaches can potentially help with the detection. The combined EM approaches are also found to explain the future stock returns better than the individual ones. Our results from the two-stage least squares (2SLS) and additional robustness checks further support our findings.

Our study contributes to the literature on EM and stock performance in several ways. First, on the top of the prior mentioned research that study the association between EM and future stock performance, we use the latest sample firms propose that the investors need different periods of time to correct earnings manipulators' stock prices. The sooner investors get over the EM impacts, the earlier stock prices are corrected. Therefore, firm managers could potentially choose EM approaches based on their future stock price expectations and investors' potential reactions.

Next, we are among the first to track the risk-adjusted investment performance measures of the stock portfolios by employing common methods used in the fund industry, for example, the M-squared, Sharpe ratio and Jensen's alpha. Previous literature suggests that EM contributes to stock volatility (Chen, Huang and Jha, 2012 and Chen, Kim and Yao, 2017), thus it is essential that we measure the stock returns of portfolios accounting for the variability caused by EM. The estimation of risk-adjusted returns provides further evidence regarding the poor subsequent stock performance of aggressive earnings manipulators. Our evidence breaks the efficiency market theory and points to the difficulty that investors still face in assessing the real effects of earnings management.

Third, investors and regulators who use AEM, REM and M-scores individually to capture EM behaviour, are found to be potentially misled. The interacted EM indicators suggested in this chapter are designed to assist investors and regulators to identify earnings manipulators more rationally and explicitly. As a result, our approach is expected to be more practical for investors and investment managers, and our findings could assist researchers in establishing the true and certain effects of EM on investors' wealth.

The rest of the chapter is organized as follows. Section 2.2 discusses the background of EM and theoretical underpinning. Section 2.3 presents the hypotheses. Section 2.4 presents the data architecture and construction of variables. While Section 2.5 introduces the methods used, Section 2.6 presents the findings, and Section 2.7 concludes the chapter.

2.2 Background of Earnings Management and theoretical underpinning

2.2.1 Background of Earnings Management

EM is a behaviour that firm managers conduct to artificially drive earnings of their companies to achieve their diversified targets. Firms manipulate earnings primarily through Accrual-based earnings management (AEM) and real activities earnings management (REM). AEM is captured and studied earlier than REM by researchers. AEM has been extensively studied following the publication of the Modified Jones (1991) model (see Subramanyam, 1996; Guay, Kothari and Watts, 1996; Xie, 2001; Kothari, 2001; Perotti and Windisch, 2017; Harris, Karl and Lawrence, 2019; Garel, Martin-Flores, Petit-Romec and Scott, 2021). After the implementation of the Sarbanes Oxley Act (SOX) in 2002, firms' engagement of EM activities gradually switches from AEM to REM (Cohen, Dey and Lys, 2008), because AEM is identified as an accounting fraud by SOX and is liable to prosecution. This starts to drive researchers' attention to EM through real activities. Later on, Roychowdhury (2006) implements three proxies that can capture REM using models developed by Dechow, Kothari and Watts (1998). His methods of evaluating REM are widely used and are further developed since then (see e.g. Li, 2010; Cohen and Zarowin, 2010; Gunny, 2010; Zang, 2012; Park, 2017).

Firms have various motives of earnings manipulation. Roychowdhury (2006) documents that firms manipulate earnings via real activities to avoid reporting negative earnings. However, Chen, Lin, Wang and Wu (2010) find that firms rarely engage in EM activities to avoid reporting annual losses; instead, they manage earnings to avoid reporting earnings decreases. Blankley, Comprix and Hong (2013) conclude that firms manipulate earnings upward to meet or beat analysts' forecasts. Firms are also found to frequently manage earnings when under pressure. Huang, Lao and McPhee (2017) find that an increase in stock liquidity encourages aggressive AEM due to pressures from takeovers and equity compensation. Du and Shen (2018) suggest that firms engage in higher EM when the performance of their peers is relatively high, i.e. a market pressure mechanism. Additionally, Fields, Gupta, Wilkins and Zhang (2018) find that firms with a large amount of short-term debt coming up for renewal are subject to a number of pressure including the inability to renew the short-term loans, or at less favourable terms among other factors, which compel them to engage in EM.

Firms tend to manipulate earnings when the cost of EM is low. Chen, Lin, Chang and Lin (2013) suggest two purposes for manipulating earnings, an informative purpose and an opportunistic purpose. The act of managing earnings to transfer favourable private information to the public is referred to as the informative purpose and the act of manipulating earnings to inflate stock prices is referred to as the opportunistic purpose. Chen, Lin, Chang and Lin (2013) propose that, in the IPO year, managers manipulate earnings in a manner that is consistent with the informative (opportunistic) purpose under low (high) information uncertainty. The positive association between information asymmetry and firms' EM practices is also documented by Chahine, Mansi and Mazboudi (2015) and Cassell, Myers and Seidel (2015).

Ali and Zhang (2015) suggest that firms tend to overstate earnings when the uncertainty surrounding firms' CEO abilities is high, which tends to occur in the early years of a CEO's tenure. In those years, investors rely on the CEO's on-the-job performance to assess his or her abilities, therefore, such CEOs are likely to manage earnings to avoid being labelled as low ability. Relatedly, Kim, Miller, Wan and Wang (2016) argue that information accessibility and institutional investors' monitoring ability are prominent determinants of EM. In the presence of information asymmetry, investors do not have access to adequate information to monitor companies' operations, which releases managers more opportunities to overstate their company earnings (Warfield, Wild and Wild 1995). Moreover, Hossain, Mitra, Rezaee and Sarath (2011) propose that firms indicted by the Securities and Exchange Commission (SEC) prior to Sarbanes-Oxley (SOX) tend to manage abnormal accruals due to the weaker governance structures in place. Recently, Yung and Root (2019) document that policy uncertainty can also increase firms' earnings management behaviour, and further impairs firms' value.

It is worth mentioning here that prior studies have investigated the unconditionally informational role of EM on stock performance using broad-based samples. Prior to the wide use of AEM, researchers often use accruals to reckon firms' EM tempts and study their signalling role (Sloan, 1996). In more recent years, Xie (2001), for instance, studies the mispricing phenomenon of accruals and the association between firms' accruals and size-adjusted abnormal returns in the following three years, using a U.S. sample from 1971 to 1992. The author documents that firms having the lowest decile of abnormal accruals (i.e. AEM) outperform firms with the highest decile of the accruals in the subsequent two years. Similarly, Li (2010) finds real earnings management negatively signals U.S. firms' subsequent three years' stock performance using available financial data from 1962 to 2008. Our study improves upon the existing empirical literature by studying both AEM and REM measures and incorporating more factors (i.e. systemic factors and risk factors) into stock returns. We further impose controls for CEO characteristics, endogeneity of EM, as well as industry and year factors that could potentially affect firms' future stock performance.

2.2.2 Theoretical underpinning

Our empirical construct is confounded on two prominent theories, viz., the intertemporal choice theory and the regulatory focus theory. The intertemporal choice theory, which is a sub-theory of decision theory (Cyert and March, 1963), is fundamental to managerial work (Laverty, 1996). This theory suggests that different choices made in the current period leads to the availability of options and diverse realized outcomes in the future. Top managers would like to highly control firms' current performance and possibly the prospect of firms' future performance as well. They tend to draw business plans that could develop the company to a larger extent. However, they constantly confront difficulties and challenges that are beyond their control and capability, thus are likely to address problems via a mechanism that is integrated with their personal preferences and experience instead of structured theories (Hambrick and Mason, 1984). Those different mechanisms distinguish the availability of options as well as distinguishing realized outcomes in the future. Although similar personal experiences shape similar pattern of managers' behaviour (Boeker, 1997), managers' personal preferences would still lead to different managerial choices or decisions that diversify firms' future options and outcomes. In addition, internal struggles and conflicts for self-commendation often exist in intertemporal choice processes (Loewenstein and Prelec, 1992), which serves multiple internal battles (Schelling, 2016) that further diverse firms' options and outcomes in the future. Consequently, we use the intertemporal choice theory to explain the diverse impact of managers EM decisions on firms' future stock performance.

The regulatory focus theory, proposed by Higgins (1997), demonstrates that when exposed to a decision-making process, individuals' preferred ways of achieving their goals are not necessarily fixed. The diverse orientations that individuals present in the process of attaining goals are called regulatory focus. There are two types of regulatory focus, promotion focus and prevention focus. (Higgins, 2000; Cho, Loibl and Geistfeld, 2014; Liao and Long, 2018). Promotion focus represents a positive and aggressive point of view towards achieving a goal. Managers with this type of focus aims at gains, accomplishment and advancement. The prevention focus represents a conservative point of view, aiming at attaining goals safely, legally through given guidelines. In other words, promotion-focused executives focus on obtaining success, whilst prevention-focused executives are concerned more about avoiding failure. A few studies have employed the regulatory focus theory on the behaviour of executives. For instance, it has been applied to explain executives' decisions on firms' environmentally friendly innovation (Liao and Long, 2018); executives' performance on employee communication's effectiveness (Fransen and ter Hoeven, 2011); executives' decisions of acquisition quantity (Gamache, McNamara, Mannor and Johnson, 2015); and different executive performance between family and nonfamily firms (Jaskiewicz and Luchak, 2013). Similarly, we employ the regulatory focus theory to explain executives' behaviour, specifically managers' decisions on EM choices.

2.3 Hypotheses development

Per the intertemporal choice theory, current choices can lead to diverse realized outcomes in the future. In our case, it refers to EM decisions could vary firms' future stock performance. Firms use AEM and REM activities to manipulate earnings in order to achieve short-term financial objectives, for instance, to avoid reporting negative earnings (Roychowdhury, 2006; Chen, Lin, Wang and Wu, 2010), to meet or beat analysts' forecasts (Blankley, Comprix and Hong, 2013), among others. Firms also manage earnings due to pressures from their business environments (Huang, Lao and McPhee, 2017; Du and Shen, 2018; Fields, Gupta, Wilkins and Zhang, 2018). These EM origins are scandals for firms, which could cost them their reputation and further affect their subsequent stock prices adversely in the long term. On the other hand, firms' EM practices are hard to detect due to low information transparency and poor monitoring (Kim, Miller, Wan and Wang, 2016). Investors are likely to scrutinize the reported financial statements of firms while the underlying EM figures are unknown to them. As a result, investors are likely to be misguided by the published numbers (Teoh, Welch and Wong, 1998). However, the artificial overvaluation caused by EM is unlikely to be sustainable, thus we would expect a price correction in the shares at a future point of time, where the price correction can be reflected by a drop of firms' share value. Additionally, manipulating earnings for short-terms benefits could divert managers' attention from sustainable strategies to improve firm profitability in the long run, which can also negatively affect firms' subsequent share prices. Accordingly, we propose the following hypothesis.

H1. Aggressive EM of all kinds leads to subsequent poor stock performance.

According to the regulatory focus theory, different individuals that accrue to different preferences leading to the same goal (Cyert and March, 1963). As for EM measures, if managers prefer flexibility, then they would probably use REM instead of AEM, because AEM can be constrained by prior year's AEM, business operations (Barton and Simko, 2002) and it has to be conducted at the end of the accounting period. REM, on the other hand, can be implemented flexibly during the accounting period (Gunny, 2010). If managers prefer security, then REM is also a better choice than AEM since REM is also harder to be detected (Franz, HassabElnaby and Lobo, 2014; Enomoto, Kimura and Yamaguchi, 2015; Vorst, 2016). In contrast, AEM has the advantage of being able to manipulate earnings even after the estimated period ends (Gunny, 2010; Enomoto, Kimura and Yamaguchi, 2015). Firms may choose AEM rather than REM to manipulate their earnings when the manipulation is urgently needed when preparing for accounting statements after the estimated period.

Furthermore, managers' choices of EM approaches not only depend on their preferences, but also relies on auditor characteristics (Cohen and Zarowin, 2010). To please auditors, managers are likely to implement EM using approaches that their auditors pay less attention towards. Consequently, individual earnings management indicators may mislead EM detection when firms' use a different approach or several approaches to drive their earnings. This could further lead to difficulties in forecasting firms' future stock performance.

In addition, regulatory focus theory suggests that participants' behaviour have either promotion-focused orientation or prevention-focused orientation. In our case, firms that have no intention to manipulate earnings but are managing earnings upwards refer to promotion-focused firms, because these firms' conduct EM to achieve ego. In contrast, intentional manipulators who engage in income-increasing EM refer to prevention-focused firms, since these firms manipulate earnings upwards to avoid failure and losses. Promotion-focused firms are more creative when facing problems than prevention-focused firms (Liao and Long, 2018). Creativity assists firms discovering resources and creating technologies that are unique and hard to imitate by their competitors (Erevelles, Horton and Fukawa, 2007). Sufficient core-technologies improve the effectiveness of management and the utility of technological diversification, which are beneficial for firms' development and performance (Kim, Lee and Cho, 2016). Therefore, promotion-focused firms and prevention-focused firms are expected to have diverse future performances, whereas using basic EM indicators (AEM and REM) can hardly diversify the differences.

Accordingly, we test the following hypothesis.

H2. Designed EM approaches could mislead firms' EM detection, causing diverse future value correction needs.

As mentioned above that basic EM approaches could mislead EM detection and harm the prediction power towards future stock performance. Therefore, distinguishing promotion-focused (unintentional EM) firms from prevention-focused (intentional EM) firms is required. Beneish's (1999) M-scores compare firms' current factors from the past, and define firms that are (1) experiencing fundamental deterioration and (2) manipulating accounting practices aggressively as highly potential earnings manipulators (Beneish, Lee and Nichols 2013). Firms that have a high likelihood of manipulating earnings can refer to those with high EM intentions, therefore, we use M-scores to capture firms' EM intentions.

We interact M-scores with basic EM proxies (AEM and REM) to generate new EM indicators. We use M-scores to identify promotion-focused firms that are defined as intentional EM manipulators by AEM and REM indicators, and remove them from the manipulator group. M-scores can help further eliminate the possibility of firms being classified as aggressive manipulators by chance. For instance, when a firm is not intended to manage earnings but is considered as an aggressive manipulator due to its high discretional accruals. As a result, the new proxies that combine EM intentions with basic EM indicators are expected to better capture firms' aggressive EM behaviour. Therefore, we expect the new proxies to better explain firms' future stock performance than individual EM indices. Accordingly, we propose our third hypothesis as follows.

H3. M-scores help to improve the prediction power of EM approaches on future stock performance.

2.4 Data characteristics and variables construction

2.4.1 Data

Firms' annual accounting data are downloaded from the COMPUSTAT database, and the monthly stock price data are obtained from the Centre for Research in Security Prices (CRSP) database. Ownership concentration and institutional ownership data are collected from the Thomson Reuters Institutional (13f) Holdings database; chief executive officers' (CEO) data are obtained from the EXECUCOMP database; and Fama-French factor data are retrieved from the Fama-French Portfolio and Factors database. EXECUCOMP data started in 1992, thus this is the start of our sample period.

The sample includes publicly listed firms on the New York Stock Exchange (NYSE), the American Stock Exchange (AMSE) and the NASDAQ Stock Exchange (NASDAQ). These firms are abstracted using COMPUSTAT stock exchange codes, 11, 12 and 14, and CRSP exchange codes, 1, 2 and 3. Then the following securities are excluded from our sample to mitigate analysis noises: American Depository Receipts (ADRs), Shares Beneficial Interest (SBI), Real Estate Investment Trusts (REITs), American Trust Components, closed-end funds and companies incorporated outside the US. In the end, only two types of stocks are considered, i.e. CRSP share codes 10 and 11. Finally, utility (SIC codes 4900-4999) and financial (SIC codes 6000-6999) institutions are further excluded due to their high state linkages and unique attributes, respectively. Our primary sample comprises 9,859 firms over the base years from 1992 to 2013. We require two-year financial data prior to each base year to compute EM indicators, thus we collect financial data from the COMPUSTAT database from the year 1990 (i.e. two years before the first base year 1992). We further obtain the share price data up to the year 2016, since we need up to 36 months of stock return data following the year 2013, to study firms that are listed in the year 2013. Overall, our full sample period is from 1990 to 2016.

We use fiscal year data for accounting information obtained from multiple databases and use calendar year stock returns collected from CRSP. We do not take any lags on accounting information because the fiscal year for different firms varies. Our results are not expected to be affected by this issue since we study up to 36-month subsequent stock performance instead of 12-month, which can help eliminate the overlap problem. Additionally, the COMPUSTAT database sets firms' fiscal year as the previous year for those that report financial statements before July and sets their fiscal year as the present year for firms that report since July. Therefore, we do not simply delay the calendar year for certain months to match the fiscal year.

Table 1 Characteristic of sample firms

Panel A presents the SIC distribution of sample firms. Panel B reports the time distribution of sample firms. In panel B, the frequency shows the number of new firms that appear in each fiscal year. There are a large number of firms in the first sample year (1992). The year 1992 comprises of firms that were listed before and during 1992 rather than new IPO firms appearing in the year. The dataset is unbalanced; therefore, in panel B the cumulative frequency for year t is not equal to the sum of cumulative frequency of year t-1 and frequency of year t. Cumulative frequency presents the number of firms that are listed on the major US stock exchanges each year. Panel C reports four main characteristics of sample firms. To reduce the impact of extreme values, all variables are winsorized at the 1% and 99% levels. Size and value characteristics are measured in millions of dollars at the end of the fiscal year.

Panel A: SIC distribution

Industry	Codes	Freq	%
Oil and Gas	13, 29	418	4.24
Construction	15, 16, 17	133	1.35
Food Products	20	215	2.18
Paper and Paper Products	24-27	312	3.16
Chemical Products	28	1074	10.89
Manufacturing	30-34	453	4.59
Computer Equipment and Services	35, 73	2345	23.79
Electronic Equipment	36	797	8.08
Transportation	37, 39, 40, 42, 44, 45	497	5.04
Scientific Instruments	38	704	7.14
Communications	48	419	4.25
Durable Goods	50	263	2.67
Retail	52-57, 59	572	5.80
Eating and Drinking Establishments	58	196	1.99
Entertainment Services	70, 78, 79	262	2.66
Health	80	282	2.86
All others	01, 10, 12, 14, 21, 22, 23, 47, 51, 72, 75, 76, 82, 83, 87, 99	937	9.50
Total		9,859	100.00

Panel B: Time distribution

Year	Frequency	%	Cumulated Frequency
1992	4,619	4.57	4,619
1993	466	4.08	4,912
1994	528	4.73	5,174
1995	925	8.37	5,784
1996	417	3.76	5,896
1997	255	2.31	5,758
1998	600	5.42	5,846
1999	159	1.44	5,452
2000	98	0.88	4,965
2001	85	0.76	4,512
2002	161	1.46	4,298
2003	158	1.40	4,120
2004	128	1.16	4,014
2005	181	1.64	3,932
2006	114	1.03	3,772
2007	134	1.21	3,613
2008	115	1.04	3,454
2009	89	0.81	3,316
2010	119	1.08	3,216
2011	168	1.52	3,181
2012	178	1.61	3,160
2013	162	1.47	3,132

Panel C: Characteristics

	Total Assets	Market Value	Book-to-Market	Sales Growth (%)
Mean	1,434.646	1,754.715	0.509	0.265
Minimum	0.67	0.826	-5.413	-0.833
Quantile 25	30.047	33.737	0.219	-0.028
Median	132.667	159.855	0.435	0.087
Quantile 75	670.239	802.203	0.772	0.267
Maximum	32,870	43,278.5	3.967	6.549
Standard Deviation	4,492.776	5,724.48	0.960	0.882
Observations	112,030	101,606	101,579	102,404

Table 1 Panel A presents the industry distribution of sample firms. There are 9,859 firms in the sample where the computer equipment and services industry contribute to the majority of sample firms (23.79%) and the construction industry contributes to the least. Table 1 Panel B shows the annual distribution of sample firms. The frequency in the year 1992 is the largest since it includes IPOs for the year as well as previous IPOs up to 1992. Cumulative frequency indicates the cumulative number of firms listed up to the given year. Note that at times the cumulative numbers decrease as we progress through the sample years, especially from 20th century onwards, reflecting a higher number of delistings than listings in certain years. Table 1 Panel C reports descriptive statistics for the sample firms' total assets ($ millions), market value (in $ millions), book-to-market ratio, and annual sales growth ratios. Their mean figures are 1,435, 1,755, 0.509 and 0.265, respectively. The means of four figures are greater than their medians, indicting they are all positively skewed. The variables are winsorized at the 1% and 99% levels, respectively.

2.4.2 Variables

This section consists of two parts. The first part introduces measures of stock performance and the second part assesses measures of EM.

Stock performance variables

This chapter uses a variety of stock performance measures including holding period returns (HPRs), value-weighted market-adjusted returns (MARs), and risk-adjusted measures.

(a) Holding period returns (HPRs)

The holding period return (HPR) evaluates the stock performance of a security over a specific investment horizon. Each year we form stock portfolios and measure the 12-, 24- and 36-months HPR using the following equation.

$$HPR_i = [\prod_{m=1}^{T}(1 + r_i^m) - 1], \qquad (1)$$

where r_i^m denotes the monthly return of stock i. T represents the estimated period, i.e. either 12 months, 24 months, or 36 months.

(b) Market-adjusted returns (MARs)

Value-weighted market-adjusted return (MAR) is computed as follows.

$$MAR_i = [\prod_{m=1}^{T}(1 + r_i^m) - 1] - [\prod_{m=1}^{T}(1 + r_m^m) - 1], \qquad (2)$$

where r_i^m denotes the monthly return of stock i; r_m^m is the monthly return of the CRSP value-weighted index; and T represents either a 12-month, 24-month or 36-month estimation period.

(c) Modigliani risk-adjusted performance (M2)

The Modigliani risk-adjusted measure (M2) is an extension of the Sharpe ratio. It is scaled up by the standard deviation of the benchmark portfolio, which in our case represents the CRSP value-weighted portfolio. This ratio allows us to measure the excess return commensurate with the risk of the stock. Note that EM causes divergence between the true and market values of a stock and is, therefore, a source of volatility in stock prices. M2 allows us to account for the variability in the stock returns while explaining the stock performance due to EM.

Following Franco (1997), the M2 is computed as follows.

$$M2 = \frac{average(r_i^m - r_f^m)}{\sigma_i} * \sigma_b + \overline{r_f}, \qquad (3)$$

where r_i^m represents the monthly return of stock i; r_f^m is defined as the corresponding risk-free one-month Treasury Bill Yield; $\overline{r_f}$ represents the average risk-free one-month Treasury Bill Yield over the corresponding period; and σ_i denotes the standard deviation of the monthly returns of security i. σ_b is the standard deviation of the excess returns of a benchmark portfolio, which is the CRSP value-weighted portfolio in our case.

Earnings management (EM) variables

We include two common methods to measure EM, i.e. accrual-based earnings management (AEM) and real earnings management (REM).

(a) Accrual-based earnings management (AEM)

A cross-sectional model is employed to estimate the discretionary accruals. The cross-sectional model is estimated for each industry-year, and we use two-digit SIC codes to determine the industry of the firm (similar to Chang and Sun (2009), Cohen and Zarowin (2010), Demirtas and Rodgers Cornaggia (2013) and Yang, Hsu and Yang (2016)). We require at least eight observations in each industry-year.

Per Jones (1991), we model accruals by the following cross-sectional model:

$$\frac{TA_{it}}{Assets_{i,t-1}} = k_1 \frac{1}{Assets_{i,t-1}} + k_2 \frac{\Delta Sales_{it}}{Assets_{i,t-1}} + k_3 \frac{PPE_{it}}{Assets_{i,t-1}} + \varepsilon_{it}, \quad (4)$$

where TA_{it} is total accrual, defined as earnings before extraordinary items and discontinued operations, minus the operating cash flows (from continuing operations) in year t. $Assets_{i,t-1}$ represents total assets of company i at time $t-1$; $\Delta Sales_{it}$ is defined as the change in revenues from the preceding year; and PPE_{it} denotes the gross value of property, plant and equipment of firm i in year t; and t is the base year.

Equation (4) is estimated for each industry year and the coefficients obtained are used to compute normal accruals (NA) as follows.

$$NA_{it} = \hat{k}_1 \frac{1}{Assets_{i,t-1}} + \hat{k}_2 \frac{\Delta Sales_{it}}{Assets_{i,t-1}} + \hat{k}_3 \frac{PPE_{it}}{Assets_{i,t-1}}. \quad (5)$$

Discretionary accruals (DA) for each firm is estimated using equation (6), i.e. it is defined as the difference between a firm's actual accruals and its estimated accruals (NA) from equation (5).

$$DA_{it} = \left(\frac{TA_{it}}{Assets_{i,t-1}}\right) - NA_{it} \quad (6)$$

A positive and large DA indicates that the company manipulates earnings aggressively, while a negative and small DA denotes that the firm manages earnings conservatively.

(b) Real earnings management (REM)

Besides accruals management, firms also engage in real activities manipulations (see Cohen and Zarowin 2010). The cash flow consequences from REM are more substantial and profound than discretionary accruals. As a result, REM may impact stock prices more significantly than accruals management does. To capture the effects of REM, we use the following three variables – abnormal cash flow from operations (ABCFO), abnormal level of production costs (ABPC) and abnormal level of discretionary expenses (ABDE).

We estimate ABCFO, ABDE and ABPC following Dechow, Kothari and Watts (1998). All models in this section are estimated by industry-year, and at least eight observations are required for each industry-year model. The industry is defined using the two-digit SIC code.

(c) Abnormal Cash Flow from Operations (ABCFO)

Abnormal cash flows result from increasing price discounts, reducing credit terms and accelerating the timing of sales recognition, among others, and are used to boost earnings in the short-term. To capture abnormal cash flow from operations, we run the following model:

$$\frac{CFO_{it}}{Assets_{i,t-1}} = k_1 \frac{1}{Assets_{i,t-1}} + k_2 \frac{Sales_{it}}{Assets_{i,t-1}} + k_3 \frac{\Delta Sales_{it}}{Assets_{i,t-1}} + \varepsilon_{it}, \quad (7)$$

where CFO_{it} represents cash flow from operations of firm i in year t; $Assets_{i,t-1}$ represents total asset of company i in year $t-1$; $Sales_{it}$ denotes revenue of firm i in year t; and $\Delta Sales_{it}$ is defined as the changes in revenues from the preceding year.

The estimated coefficients ($\hat{k}_1$, $\hat{k}_2$ and $\hat{k}_3$) from equation (7) are used to compute the expected cash flow from operations (ECFO) as shown in equation (8). Abnormal CFO (ABCFO) is then computed as the actual CFO ($\frac{CFO_{it}}{Assets_{i,t-1}}$) minus the expected CFO (ECFO). A positive (negative) ABCFO indicates a downwards (upwards) earnings manipulation.

$$ECFO = \hat{k}_1 \frac{1}{Assets_{i,t-1}} + \hat{k}_2 \frac{Sales_{it}}{Assets_{i,t-1}} + \hat{k}_3 \frac{\Delta Sales_{it}}{Assets_{i,t-1}}. \quad (8)$$

(d) Abnormal Level of Production Costs (ABPC)

Firms can manipulate their earnings by lowering the cost of their goods sold, which is captured by their abnormal level of production cost (ABPC). ABPC is estimated as follows. First, we calculate the production cost (PROD) by integrating the cost of goods sold (COGS) and the changes in inventory (ΔINV_{it}). Next, we model PROD over total assets using the following model.

$$\frac{PROD_{it}}{Assets_{i,t-1}} = k_1 \frac{1}{Assets_{i,t-1}} + k_2 \frac{Sales_{it}}{Assets_{i,t-1}} + k_3 \frac{\Delta Sales_{it}}{Assets_{i,t-1}} + k_4 \frac{\Delta Sales_{i,t-1}}{Assets_{i,t-1}} + \varepsilon_{it} \quad (9)$$

Then, the expected level of production cost (EPC) is calculated as follows, using coefficients obtained from Equation (9):

$$EPC_{it} = \hat{k}_1 \frac{1}{Assets_{i,t-1}} + \hat{k}_2 \frac{Sales_{it}}{Assets_{i,t-1}} + \hat{k}_3 \frac{\Delta Sales_{it}}{Assets_{i,t-1}} + \hat{k}_4 \frac{\Delta Sales_{i,t-1}}{Assets_{i,t-1}}, \quad (10)$$

ABPC refers to the difference between the actual production costs over total assets ($\frac{PROD_{it}}{Assets_{i,t-1}}$) and the expected level of production costs (EPC). An increase in production costs implies overproduction, in which case, firms increase the inventory while reducing the cost of goods sold. Therefore, a positive (negative) ABPC indicates an upwards (downwards) earnings manipulation.

(e) Abnormal Level of Discretionary Expenses (ABDE)

Firms can also manage earnings via manipulating advertising, research and development, and selling, general and administrative expenses – i.e. collectively referred to as discretionary expenses. We conduct equation (11) to model the actual level of discretionary expenses (DISX), and abnormal discretionary expenses (ABDE) is the difference between actual discretionary expenses over total assets ($\frac{DISX_{it}}{Assets_{i,t-1}}$) and expected discretionary expenses (EDE) obtained from equation (12).

$$\frac{DISX_{it}}{Assets_{i,t-1}} = k_1 \frac{1}{Assets_{i,t-1}} + k_2 \frac{Sales_{i,t-1}}{Assets_{i,t-1}} + \varepsilon_{it}, \tag{11}$$

$$EDE_{it} = \hat{k}_1 \frac{1}{Assets_{i,t-1}} + \hat{k}_2 \frac{Sales_{i,t-1}}{Assets_{i,t-1}} \tag{12}$$

where $DISX_{it}$ denotes the discretionary expenditures of firm i in year t, defined as the sum of research and development expenses (R&D), advertising expenses (A&D), and selling, general and administrative expenses (SG&A). A positive (negative) ABDE indicates a downwards (upwards) earnings manipulation.

2.5 Methodology and estimation

In this section, we present in various test procedures with a view of the EM and long-term performance association. We also discuss in details the identification of earnings-suspect firms and describe strategies for robustness exercise.

2.5.1 Comparisons of long-term performance

We group sample firms in portfolios based on their EM scores (i.e., either DA, ABCFO, ABPC and ABDE) in each industry-year. The ranking starts with the lowest EM score to the highest in year t, and the ranked firms are partitioned into five quintiles, which is suggested by Li (2010). Our portfolio-sorted analysis is, therefore, based on full-sample-breakpoints using our estimated EM scores. Following year t, the mean and median 12 months', 24 months' and 36 months' stock performance measures for each portfolio/quintile are tracked and compared. The lowest quintile of DA and ABPC comprises firms that are least likely to manipulate earnings upwards (conservative), and the highest quintile contains firms that are most likely to manage earnings upwards (aggressive). The interpretation is reversed in the cases of ABCFO and ABDE, i.e. the lowest-quintile firms are aggressive manipulators as opposed to the highest-quintile ones. The mean and median values of subsequent 12-, 24- and 36-month performance variables are compared and contrasted between the top and bottom quintiles using the t-test and the Wilcoxon signed ranked test.[3] We include nonparametric Wilcoxon signed ranked tests in addition to t-test in means, since our quintile groups may not be normally distributed.

2.5.2 Earnings management and long-term performance

Multivariate analyses are then conducted to study the impact of EM on firms' long-term performance with a control of additional firm attributes that may also affect their long-term performance. We use HPRs, MARs, and M2 to measure the long-term performance (i.e. dependent variable), where M2 is a risk-adjusted return measure. The ordinary least squared (OLS) regression model is applied, as shown in equation (13). The year and the industry effects are fixed in the model. The Fama-French 48-industry classification is used to identify and classify industries, and robust standard errors are applied.

To study the impact of EM comprehensively, various EM variables (the main independent variables of interest) are used. First, the raw scores of EM indicators are adopted to provide a general view of EM on long-term performance. Second, dummy variables representing firms that belong to the most aggressive portfolio/quintile are used. Lastly, a dummy variable representing firms that belong to the most conservative portfolio/quintile is used. We conduct regressions using the most and the least aggressive quintile dummies respectively, because these two variables are likely to be correlated, causing multicollinearity.

$$\begin{aligned} Longterm\ performance_{i,t} &= \alpha_0 + \alpha_1 Earnings\ management_{i,t} \\ &+ \alpha_2 lag(Longterm\ performance)_{i,t} + \alpha_3 Stock\ liquidity_{i,t} \\ &+ \alpha_4 Logsize_{i,t} + \alpha_5 Leverage_{i,t} + \alpha_6 ROA_{i,t} + \alpha_7 BTM_{i,t} \\ &+ \alpha_8 Ownership_{i,t} + \alpha_9 Institutionown_{i,t} + \alpha_{10} CEOown_{i,t} \\ &+ \alpha_{11} Exeage_{i,t} + \alpha_{12} Bigaudit_{i,t} + \alpha_{13} Hightech_i + \varepsilon_{i.t} \end{aligned} \tag{13}$$

[3] The portfolios are rebalanced every year. Thus, the same firm may be classified differently from one year to the next and/or remain in the same portfolio over several years. In the following sections, we explain how this is accounted for using multiple regression techniques and other measures.

where the $Longterm\ performance_{i,t}$ represents 12-month, 24-month or 36-month stock performance. The long-term performance is measured by HPRs, MARs and M2, respectively. $Earnings\ management_{i,t}$ takes a range of values based on DA, ABCFO, ABPC and ABDE, respectively. We conduct three regressions for each EM indicator, where the first regression uses the continuous values of EM. In the second regression, dummy_lowest is applied to represent stocks in the lowest EM quintile group. We set dummy_lowest as one for banks in the lowest quintile of an EM indicator, zero otherwise. The third regression uses dummy_highest to capture stocks in the highest EM quintile group. We set dummy_highest as one for banks in the highest quintile of an EM indicator, zero otherwise.

Considering the attributes of the EM indicators, dummyda_highest, dummyabcfo_lowest, dummyabpc_highest and dummyabde_lowest are applied to test aggressive earnings manipulators, and dummyda_lowest, dummyabcfo_highest, dummyabpc_lowest and dummyabde_highest are used to estimate conservative earnings manipulators. We expect the signs of those two sets of dummy variables to diverge, i.e. the coefficients of the dummy variables representing aggressive (conservative) firms to be negative (positive). The first lag of the performance measures ($lag(Longterm\ performance)$) are included in all of our models to control for the dynamic impacts and the remainder of the variables are defined in Appendix AI.

2.5.3 Identification issues

We classify firms' EM behaviour based on the deviations between actual accounting proxies and their expected values. However, these deviations could be misled for a number of reasons including the fact that certain firms are rated as manipulators due to their unconventional business strategies. Besides, there can be some unobserved factors that lead a firm to fall into a specific quintile/portfolio as per our ranking and assumptions, and yet is not necessarily managing earnings in the way assumed. Per Gunny (2010), without considering the incentives of managers, there exists the possibility that the estimated EM variables may be identifying other behaviour instead of intentional manipulations. To account for this possibility, we consider the Beneish M-model.

The Beneish's (1999) Model is widely applied for ascertaining a firm's probability of manipulating earnings upwards (Anh and Linh, 2016; Khan and Akter, 2017). Per Beneish (1999), an intended manipulator is a firm with a M-score greater than or equal to -1.78. The model is as follows.

$$\begin{aligned} M - score_t = & -4.84 + 0.92 \times DSRI_t + 0.528 \times GMI_t + 0.404 \times AQI_t + 0.892 \times SGI_t \\ & + 0.115 \times DEPI_t - 0.172 \times SGAI_t + 4.679 \times TATA_t - 0.327 \times LVGI_t \end{aligned} \tag{14}$$

where DSRI is the Days Sales in Receivable Index; GMI denotes a Gross Margin Index; AQI represents an Asset Quality Index; SGI denotes a Sales Growth Index; DEPI represents a Depreciation Index; SGAI is a Sales General and Administrative Expenses Index; TATA is the ratio of Total Accruals to Total Assets; and LVGI represents a Leverage Index. The detailed variable specifications are reported in Appendix AI. We compare and contrast the stock performance of intentional manipulators and non-intentional firms together with our pre-defined EM indicators. We also control for firms' M-scores in the multiple regressions of firm performance by interacting an M-score dummy with aggressive dummies of DA, ABCFO, ABPC and ABDE indices, respectively. The M-score dummy is defined as one for firms with an M-score greater than or equal to -1.78, zero otherwise.

2.5.4 Endogenous controls

It is conceivable that various firm characteristics, for instance, organizational and environmental uncertainties, may influence firms' long-term stock performance via managerial financial reporting behaviour. To address this concern, we use an Instrumental Variable approach. Hazarika, Karpoff, and Nahata (2012) suggest the use of the sum of extraordinary items and special items (special items) as instruments. Additionally, firms' research and development expenditure (R&D), and changes in their yearly value of property, plant and equipment (ΔPPE) can also be considered as potential instruments because they are found to have an explanatory power towards EM but are not correlated with the long-term performance indicators in our models. Therefore, this chapter uses special items, R&D and ΔPPE as instruments for EM.

The instruments--special items, R&D and ΔPPE are used in a two-stage least squares (2SLS) regression setting—Equations (15) and (16). Equation (15) represents the first-stage regression model, and equation (16) represents the second-stage regression model. To be consistent with our baseline analysis, the year and industry effects are fixed in 2SLS regressions. The Fama-French 48-industry classification is used to identify and classify industries, and robust standard errors are adopted.

$$\begin{aligned} Earnings\ management *_{i,t} &= \beta_0 + \beta_1 Special\ items_{i,t} + \beta_2 LogRD_{i,t} + \beta_3 \Delta PPE_{i,t} \\ &+ \beta_4 lag(Earnings\ management\ *)_{i,t} + \beta_5 Stock\ liquidity_{i,t} \\ &+ \beta_6 Logsize_{i,t} + \alpha_7 Leverage_{i,t} + \alpha_8 ROA_{i,t} + \beta_9 BTM_{i,t} \\ &+ \beta_{10} Ownership_{i,t} + \beta_{11} Institutionown_{i,t} + \beta_{12} CEOown_{i,t} \\ &+ \beta_{13} Exeage_{i,t} + \beta_{14} Bigaudit_{i,t} + \beta_{15} Hightech_i + \varepsilon_{i.t} \end{aligned} \tag{15}$$

$$\begin{aligned} Longterm\ performance_{i,t} &= \alpha_0 + \alpha_1 Earnings\ management\ *_{i,t} \\ &+ \alpha_2 lag(Longterm\ performance)_{i,t} + \alpha_3 Stock\ liquidity_{i,t} \\ &+ \alpha_4 Logsize_{i,t} + \alpha_5 Leverage_{i,t} + \alpha_6 ROA_{i,t} + \alpha_7 BTM_{i,t} \\ &+ \alpha_8 Ownership_{i,t} + \alpha_9 Institutionown_{i,t} + \alpha_{10} CEOown_{i,t} \\ &+ \alpha_{11} Exeage_{i,t} + \alpha_{12} Bigaudit_{i,t} + \alpha_{13} Hightech_i + \varepsilon_{i.t} \end{aligned} \tag{16}$$

Where $Earnings\ management\ *_{i,t}$ takes a range of values based on DA, ABCFO, ABPC, ABDE and their interactions with the M-score, respectively. Definition of control variables are displayed in Appendix AI.

2.6 Empirical analyses

This section reports the empirical analysis results. To start with, the descriptive statistics of our main variables are reported in Table 2. All the variables are winsorized at the 1% and 99% levels, except Bigaudit and Hightech. According to the data availability, ABDE only has 24,579 accessible observations. An inclusion of CEO characteristics could lead to a further observation decrease in our estimations, which may cause noises in our analysis.

2.6.1 Univariate Analyses

Performance of Stock Portfolios Based on Discretionary Accruals

The univariate test results of discretionary accruals (DA) on firms' 12-month, 24-month and 36-month subsequent long-term performance are reported in Tables 3. Q1 (Q5) is the portfolio of firms that manage earnings the least (most) and is defined as conservative (aggressive) firms. Differences in means of both HPRs and MARs are significantly positive (at the 10% level) for up to 36 months and the differences between Q1 and Q5 grow with time. This indicates that when firms use accruals to manipulate earnings, conservative members outperform aggressive ones in raw returns (HPRs) and returns that consider systematic factors (MARs) in the following 36 months.

Table 2 Descriptive statistics of sample firms

This table presents descriptive statistics of sample firms across the period 1990 to 2016. All variables are winsorized at the 1% and 99% levels except Bigaudit and Hightech to eliminate the impacts of extreme values. Variable definitions are provided in Appendix AI.

Variable	Mean	Minimum	Quantile 25	Median	Quantile 75	Maximum	Std.dev	Observations
Holding period returns (HPRs)	0.115	-0.881	-0.275	0.028	0.368	3.533	0.703	91,135
Market adjusted returns (MARs)	0.036	-0.970	-0.360	-0.073	0.241	3.313	0.672	91,135
Modigliani risk-adjusted performance (M2)	0.004	-0.042	-0.003	0.005	0.012	0.040	0.014	90,437
Sharpe ratio	0.056	-0.899	-0.154	0.069	0.278	0.893	0.388	90,437
Jensen alpha	0.008	-0.146	-0.020	0.006	0.032	0.203	0.055	91,105
DA	-0.001	-1.550	-0.063	0.011	0.084	1.355	0.322	104,016
ABCFO	0.012	-1.424	-0.063	0.022	0.118	0.952	0.291	104,623
ABPC	-0.005	-0.900	-0.146	-0.005	0.132	0.986	0.290	96,188
ABDE	-0.054	-4.116	-0.202	-0.042	0.111	1.900	0.607	24,579
Special items	-0.023	-0.587	-0.014	0.000	0.00	0.196	0.088	109,331
LogR&D	2.023	-3.244	0.663	2.045	3.356	7.390	2.082	57,459
DeltaPPE	40.053	-932.9	0.033	2.528	20.73	1630	246.075	110,929
Stock liquidity	-0.043	-2.702	-0.023	0.0004	0.014	1.655	0.425	91,180
Logsize	4.971	-0.337	3.405	4.889	6.509	10.400	2.248	111,969
Leverage	0.335	-0.782	0.015	0.244	0.506	2.661	0.441	111,470
ROA	-0.112	-2.812	-0.101	0.022	0.072	0.334	0.440	111,530
BTM	0.509	-5.413	0.219	0.435	0.772	3.967	0.960	101,579
Ownership	0.204	0.021	0.052	0.103	0.248	1	0.239	74,155
Institutionown	0.445	0.001	0.171	0.433	0.701	1.066	0.301	73,587
CEOown	3.597	0	0.022	0.779	3	36.9	6.956	21,214
Exeage	67.550	46	60	67	74	91	9.748	31,269
Bigaudit	0.742	0	0	1	1	1	0.438	112,030
Hightech	0.114	0	0	0	0	1	0.318	112,030
M-score	-2.289	-9.037	-2.983	-2.590	-2.129	14.933	2.544	57,337

Differences in medians of HPRs and MARs between Q1 and Q5 quintiles are overall consistent with the mean differences of HPRs and MARs, except the negative differences of the 12-month HPRs (-0.016) and MARs (-0.018). We assume the unexpected signs are due to HPRs' and MARs' distribution differences between Q1 and Q5 before considering risks. After taking the risks into account, the differences in means and medians of M2 between Q1 and Q5 groups are significantly positive (at the 5% level or better) for up to 24 months, which fits our expectation that aggressive firms underperform conservative firms subsequently. This finding has also been suggested by Xie (2001).

Table 3 Discretionary Accruals (DA) and long-term stock performance

This table reports the univariate analysis results of mean and median stock long-term performance by Discretionary Accruals (DA) quintiles. The long-term performance is measured by holding period returns (HPRs), market adjusted returns (MARs) and Modigliani risk-adjusted performance (M2), respectively. The estimated period ranges from 12 months to 36 months, beginning from the year following the EM ranking (base) year. DA is ranked by quintiles in each industry-year, and each industry-year has at least eight observations. Quintile 1 (Q1) firms manage earnings conservatively and Quintile 5 (Q5) firms manage earnings aggressively, based on the DA measured in the base year. T-test and Wilcoxon test of the differences in mean and median, respectively, are presented.

Quintile		HPRs			MARs			M2		
		12 months	24 months	36 months	12 months	24 months	36 months	12 months	24 months	36 months
Q1 (Conservative)	Mean	0.177	0.435	0.601	0.065	0.195	0.226	0.003	0.016	0.003
	Median	-0.038	0.029	0.052	-0.144	-0.179	-0.260	0.005	0.015	0.008
	Obs.	17,643	12,986	11230	17643	12986	11230	15267	12980	5344
Q2	Mean	0.177	0.394	0.594	0.063	0.154	0.218	0.004	0.016	0.006
	Median	0.045	0.125	0.198	-0.068	-0.093	-0.134	0.006	0.015	0.011
	Obs.	19,578	15,502	13791	19578	15502	13791	17527	15502	7272
Q3	Mean	0.169	0.383	0.579	0.055	0.145	0.207	0.005	0.015	0.007
	Median	0.058	0.137	0.220	-0.051	-0.077	-0.105	0.006	0.014	0.011
	Obs.	19,648	15,938	14247	19648	15938	14247	17895	15938	7861
Q4	Mean	0.161	0.348	0.543	0.048	0.112	0.171	0.004	0.014	0.006
	Median	0.044	0.100	0.172	-0.061	-0.101	-0.140	0.005	0.013	0.011
	Obs.	19,721	15,957	14271	19721	15957	14271	17929	15955	7663
Q5 (Aggressive)	Mean	0.138	0.293	0.442	0.025	0.053	0.066	0.003	0.011	0.004
	Median	-0.022	-0.002	0.023	-0.126	-0.208	-0.278	0.004	0.010	0.008
	Obs.	17,828	14,140	12560	17828	14140	12560	16139	14139	6115
Q1 minus Q5	Mean	0.039***	0.141***	0.160***	0.039***	0.142***	0.161***	0.001**	0.005***	-0.001
	Median	-0.016***	0.031***	0.029***	-0.018**	0.029***	0.018***	0.001***	0.005***	0.000

* indicates statistical significance at the 10% level.
** indicates statistical significance at the 5% level.
*** indicates statistical significance at the 1% level.

Performance of Stock Portfolios Based on Real Earnings Management

We now proceed to the analysis of the REM variables. We first test the effect of abnormal cash flow from operations (ABCFO) on future stock performance in Tables 4. Quintile 1 represents income-increasing earnings manipulators and Quintile 5 represents income-decreasing earnings manipulators based on ABCFO. In the 12 months following the portfolio formation, the means of HPRs, MARs and M2 from Quintile 5 are significantly higher than that from Quintile 1, suggesting an inverse association between ABCFO and 12-month stock returns. This association is also observed by Li (2010) using data from 1962 to 2008. We further observe a decline regarding the impact of ABCFO on stock returns after 12 months, based on t-tests in means. Results from Wilcoxon Signed tests are all positive and significant at the 10% level or better, suggesting that conservative portfolios' 12-, 24- and 36-month median returns significantly exceed the corresponding figures from the aggressive portfolios, respectively. Overall, the evidence suggests that stimulate earnings via abnormally decreasing operating cash flows yields inferior future stock performance, especially towards the subsequent 12 months.

We then study the effect of abnormal production costs (ABPC) in Table 5. Quintile 1 represents conservative earnings manipulators and Quintile 5 represents aggressive earnings manipulators. The differences in the mean and median of the 12-, 24- and 36-month HPRs, MARs and M2 between Q1 and Q5 are positive and mostly significant (at the 10% level or better), apart from the differences of 36-month M2. The results highly fit our expectation that firms with abnormally large production costs achieve lower future stock returns than firms having abnormally small production costs, and is consistent with findings from Li (2010) that firms with a high level of ABPC underperform their peers in the subsequent three years. We also observe that the mean differences of stock returns between Q1 and Q5 are generally more significant in the subsequent 12 months than in the 24-month and 36-month periods. The differences in medians of future stock returns increase gradually during the subsequent 36 months, when risks are not considered in returns.

Table 4 Abnormal cash flow from operations (ABCFO) and long-term stock performance

This table reports the univariate analysis results of mean and median stock long-term performance by abnormal cash flow from operations (ABCFO) quintiles. The long-term performance is measured by holding period returns (HPRs), market adjusted returns (MARs) and Modigliani risk-adjusted performance (M2), respectively. The estimated period ranges from 12 months to 36 months, beginning from the year following the EM ranking (base) year. ABCFO is ranked by quintiles in each industry-year, and each industry-year has at least eight observations. Quintile 1 (Q1) firms manage earnings aggressively and Quintile 5 (Q5) firms manage earnings conservatively, based on the ABCFO measured in the base year. T-test and Wilcoxon test of the differences in mean and median, respectively, are presented.

Quintile		HPRs			MARs			M2		
		12 months	24 months	36 months	12 months	24 months	36 months	12 months	24 months	36 months
Q1 (Aggressive)	Mean	0.122	0.352	0.497	0.010	0.109	0.110	0.001	0.012	0.015
	Median	-0.106	-0.117	-0.107	-0.215	-0.322	-0.430	0.003	0.010	0.013
	Obs.	17,789	12,942	11,105	17,789	12,942	11,105	15,465	12,939	11,104
Q2	Mean	0.170	0.399	0.587	0.055	0.155	0.205	0.004	0.016	0.017
	Median	0.007	0.073	0.134	-0.102	-0.140	-0.187	0.005	0.014	0.015
	Obs.	19,451	14,912	13,090	19,451	14,912	13,090	17,270	14,911	13,090
Q3	Mean	0.168	0.369	0.578	0.054	0.130	0.205	0.005	0.015	0.016
	Median	0.041	0.122	0.201	-0.066	-0.085	-0.124	0.005	0.014	0.015
	Obs.	19,567	15,689	13,967	19,567	15,689	13,967	17,709	15,688	13,967
Q4	Mean	0.174	0.376	0.568	0.059	0.139	0.199	0.005	0.015	0.016
	Median	0.067	0.144	0.228	-0.043	-0.070	-0.083	0.006	0.014	0.015
	Obs.	19,773	16,206	14,611	19,773	16,206	14,611	17,985	16,204	14,609
Q5 (Conservative)	Mean	0.185	0.353	0.522	0.075	0.122	0.159	0.005	0.014	0.015
	Median	0.060	0.112	0.168	-0.046	-0.087	-0.136	0.006	0.014	0.014
	Obs.	18,283	15,077	13,585	18,283	15,077	13,585	16,685	15,075	13,584
Q5 minus Q1	Mean	0.063***	0.001	0.025	0.065***	0.014	0.049*	0.004***	0.002***	0.000
	Median	0.166***	0.229***	0.275***	0.169***	0.235***	0.294***	0.003***	0.004***	0.001*

* indicates statistical significance at the 10% level.
** indicates statistical significance at the 5% level.
*** indicates statistical significance at the 1% level.

Table 5 Abnormal production costs (ABPC) and long-term stock performance

This table reports the univariate analysis results of mean and median long-term stock performance by abnormal production costs (ABPC) quintiles. The long-term performance is measured by holding period returns (HPRs), market adjusted returns (MARs) and Modigliani risk-adjusted performance (M2), respectively. The estimated period ranges from 12 months to 36 months, beginning from the year following the EM ranking (base) year. ABPC is ranked by quintiles in each industry-year, and each industry-year has at least eight observations. Quintile 1 (Q1) firms manage earnings conservatively and Quintile 5 (Q5) firms manage earnings aggressively, based on the ABPC measured in the base year. T-test and Wilcoxon test of the differences in mean and median, respectively, are presented.

Quintile		HPRs			MARs			M2		
		12 months	24 months	36 months	12 months	24 months	36 months	12 months	24 months	36 months
Q1 (Conservative)	Mean	0.193	0.389	0.568	0.079	0.152	0.196	0.004	0.015	0.016
	Median	0.049	0.103	0.164	-0.062	-0.107	-0.151	0.005	0.015	0.015
	Obs.	17,017	13,606	12,135	17,017	13,606	12,135	15,328	13,605	12,134
Q2	Mean	0.181	0.399	0.577	0.067	0.161	0.207	0.005	0.016	0.016
	Median	0.049	0.131	0.200	-0.059	-0.083	-0.109	0.005	0.015	0.015
	Obs.	17,985	14,309	12,747	17,985	14,309	12,747	16,213	14,307	12,747
Q3	Mean	0.170	0.387	0.589	0.057	0.151	0.221	0.005	0.015	0.016
	Median	0.042	0.123	0.191	-0.066	-0.089	-0.126	0.005	0.014	0.015
	Obs.	17,755	13,954	12,444	17,755	13,954	12,444	15,834	13,951	12,444
Q4	Mean	0.170	0.383	0.548	0.056	0.144	0.174	0.004	0.015	0.016
	Median	0.023	0.089	0.157	-0.089	-0.115	-0.166	0.005	0.014	0.015
	Obs.	17,834	13,937	12,392	17,834	13,937	12,392	15,974	13,937	12,392
Q5 (Aggressive)	Mean	0.146	0.351	0.513	0.033	0.113	0.143	0.003	0.014	0.016
	Median	-0.030	0.019	0.059	-0.135	-0.181	-0.245	0.004	0.012	0.014
	Obs.	16,924	12,985	11,502	16,924	12,985	11,502	14,991	12,982	11,499
Q1 minus Q5	Mean	0.047***	0.038*	0.055**	0.046***	0.038*	0.053**	0.001***	0.001**	0.0003
	Median	0.079***	0.084***	0.105***	0.073***	0.074***	0.094***	0.001***	0.003***	0.001

* indicates statistical significance at the 10% level.
** indicates statistical significance at the 5% level.
*** indicates statistical significance at the 1% level.

Finally, we investigate the effect of abnormal discretionary expenses (ABDE) in Tables 6. Quintile 1 represents income-increasing manipulators and Quintile 5 represents income-decreasing manipulators. The results show negative differences of future stock returns between conservative and aggressive manipulators. The differences in means of 12-, 24- and 36-month M2 and the differences in medians of 12-, 24- and 36-month HPRs and MARs, between Q5 and Q1 are statistically significant (at the 10% level or better). These results suggest that the future returns of firms that claim abnormally less discretionary expenses exceed the future returns of firms that announce abnormally more discretionary expenses, which is not consistent with our Hypothesis 1. Discretionary expenses are used to improve employees' wellbeing, which are “unnecessary” expenses for companies' operations. It is possible that managers claim abnormally large discretionary expenses for their own benefits, or firms with large ABDE concentrate more on employees' benefits rather than shareholders'. Therefore, a relatively negative association between firms' ABDE and future stock returns is presented in the analysis.

Table 6 Abnormal discretionary expenses (ABDE) and long-term stock performance

This table reports the univariate analysis results of mean and median long-term stock performance by abnormal discretionary expenses (ABDE) quintiles. The long-term performance is measured by holding period returns (HPRs), market adjusted returns (MARs) and Modigliani risk-adjusted performance (M2), respectively. The estimated period ranges from 12 months to 36 months, beginning from the year following the EM ranking (base) year. ABDE is ranked by quintiles in each industry-year, and each industry-year has at least eight observations. Quintile 5 (Q5) firms manage earnings conservatively and Quintile 1 (Q1) firms manage earnings aggressively, based on the ABDE measured in the base year. T-test and Wilcoxon test of the differences in mean and median, respectively, are presented.

Quintile		HPRs			MARs			M2		
		12 months	24 months	36 months	12 months	24 months	36 months	12 months	24 months	36 months
Q1 (Aggressive)	Mean	0.183	0.412	0.603	0.086	0.203	0.270	0.004	0.016	0.017
	Median	0.029	0.098	0.166	-0.075	-0.078	-0.129	0.005	0.014	0.015
	Obs.	3,973	3,074	2,726	3,973	3,074	2,726	3,543	3,073	2,726
Q2	Mean	0.162	0.367	0.557	0.062	0.156	0.222	0.005	0.015	0.016
	Median	0.054	0.129	0.220	-0.038	-0.059	-0.087	0.005	0.015	0.015
	Obs.	4,828	3,836	3,431	4,828	3,836	3,431	4,340	3,836	3,431
Q3	Mean	0.157	0.359	0.528	0.058	0.149	0.194	0.005	0.015	0.016
	Median	0.039	0.119	0.197	-0.059	-0.070	-0.110	0.005	0.016	0.016
	Obs.	4,722	3,745	3,295	4,722	3,745	3,295	4,225	3,745	3,295
Q4	Mean	0.165	0.383	0.565	0.068	0.191	0.229	0.002	0.014	0.016
	Median	0.017	0.087	0.171	-0.074	-0.110	-0.141	0.005	0.015	0.016
	Obs.	4,875	3,825	3,349	4,875	3,825	3,349	4,370	3,824	3,349
Q5 (Conservative)	Mean	0.169	0.371	0.565	0.073	0.164	0.234	0.003	0.013	0.015
	Median	-0.015	0.019	0.073	-0.103	-0.167	-0.225	0.004	0.013	0.015
	Obs.	4,317	3,335	2,913	4,317	3,335	2,913	3,867	3,334	2,913
Q5 minus Q1	Mean	-0.014	-0.041	-0.039	-0.012	-0.039	-0.036	-0.001*	-0.003**	-0.002*
	Median	-0.044**	-0.079***	-0.093***	-0.028**	-0.089***	-0.096***	-0.001*	-0.001	0.000

* indicates statistical significance at the 10% level.
** indicates statistical significance at the 5% level.
*** indicates statistical significance at the 1% level.

To sum up, the difference in mean tests in this section show that DA and ABCFO mainly affect non-financial firms' subsequent 12-month stock returns. ABPC can influence firms' subsequent stock performance for up to 24 months and the impact of ABDE on firms' future stock returns is overall insignificant. These findings are consistent with Li (2010), who also find that different approaches of EM have different impact periods towards firms' future stock returns. Our findings suggest that investors have different reactions towards different approaches of EM and the price correction occurs at different future periods for firms that use different EM methods. Our findings also indicate that ABPC has a longer impact on firms' stock prices than AEM, ABCFO and ABDE. This could be due to the reason that production cost manipulations generate excessive inventories, which is likely to lead to additional inventory carrying costs in the following accounting year, affecting earnings subsequently, whereas other types of earnings manipulation methods mainly act on current period earnings.

2.6.2 Multivariate Analyses

Benchmark estimation

Table 7 presents the results of multivariate analyses. Panel A to Panel D report results based on different EM matrices, i.e. discretionary accruals (DA), abnormal cash flow from operations (ABCFO), abnormal production costs (ABPC) and abnormal discretionary expenses (ABDE), respectively. To conserve space, we only report the coefficients of the EM proxies in the regressions of stock returns.[4]

The coefficients of DA are positive for all types of future stock returns and the positive impacts are statistically significant for the 36-month returns. For the fact that the positive impacts of DA on firms' 12- and 24-month returns are insignificant, we expect that the significantly positive impacts on the 36-month returns could be driven by some omitted variables or uncontrolled circumstances, such as the endogeneity of DA. The coefficients of Dummyda_lowest are positive and that of Dummyda_highest are negative, especially for the subsequent 24 months, which fits our expectations. These results suggest that conservative firms classified by DA have higher subsequent stock performance than their counterparts, whilst aggressive firms classified by DA have lower subsequent stock performance than their counterparts during the subsequent 12- and 24-month periods.

Results from REM measures show that ABCFO and ABDE have positive impacts on future stock returns and ABPC is found negatively associated with future stock performance, especially during the subsequent 12 months. As for dummy variables that representing income-increasing (aggressive) and income-decreasing (conservative) REM, we find that, in general, conservative dummies present positive coefficients whereas aggressive dummies have negative coefficients. These findings provide evidence that, as expected, conservative firms generally achieve higher future stock returns than their counterparts but aggressive firms normally underperform their counterparts. However, not all associations between REM and future stock returns are statistically significant.

[4] The findings on the coefficients of the control variables are available upon request from the authors.

Table 7 Earnings management and long-term stock performance

Table 7 Earnings management and long-term performance

This table reports coefficients of EM proxies from Ordinary Least Square (OLS) regressions. The dependent variable is the long-term stock performance, measured by holding period returns (HPRs), market adjusted returns (MARs) and Modigliani risk-adjusted performance (M2), respectively. The estimated period ranges from 12 months to 36 months, beginning from the year following the EM ranking (base) year. Panel A to Panel D report results based on different EM proxies, i.e. discretionary accruals, abnormal cash flow from operations, abnormal production costs and abnormal discretionary expenses, respectively. Models (1), (4), (7) and (10) use continuous variables as EM indicators; and models (2), (3), (5), (6), (8), (9), (11) and (12) use dummy variables as EM matrices. The dummy_highest is valued as one if the corresponding EM measure lies in its highest quintile (Q5), zero otherwise; and the dummy_lowest is valued one if the corresponding measure lies in its lowest quintile (Q1), zero otherwise. Year and industry effects are fixed, and robust errors are controlled for in all models. Fama-French 48-industry identification codes are applied to control for industry effects and all control variables are applied in all models.

		HPRs			MARs			M2		
	Independent variables	12 months	24 months	36 months	12 months	24 months	36 months	12 months	24 months	36 months
Panel A Discretionary Accruals (DA)										
(1)	DA	0.003	0.007	0.087**	0.002	0.007	0.088**	0.000	-0.0005	0.001**
(2)	Dummyda_highest (aggressive)	-0.030*	-0.062***	-0.073***	-0.030*	-0.062***	-0.073***	-0.002***	-0.002***	-0.0001
(3)	Dummyda_lowest (conservative)	0.032**	0.066***	0.040	0.033**	0.066***	0.041	0.001**	0.002***	0.000
	Observations	17,742	13,961	12,217	17,742	13,961	12,217	15,907	13,961	12,217
Panel B Abnormal Cash Flow from Operations (ABCFO)										
(4)	ABCFO	0.051	0.110**	0.013	0.061*	0.110**	0.013	0.002***	0.002	-0.001
(5)	Dummyabcfo_highest (conservative)	0.026**	0.053**	0.015	0.029***	0.052**	0.015	0.001***	0.001	-0.001
(6)	Dummyabcfo_lowest (aggressive)	-0.027	-0.059*	-0.005	-0.030	-0.059*	-0.005	-0.002***	-0.002	0.0001
	Observations	17,792	14,004	12,255	17,792	14,004	12,255	15,954	14,004	12,255
Panel C Abnormal Production Costs (ABPC)										
(7)	ABPC	-0.055**	-0.053	-0.073	-0.054**	-0.063	-0.073	-0.002***	0.001	-0.0002
(8)	Dummyabpc_highest (aggressive)	-0.026*	-0.058**	-0.061*	-0.026*	-0.058**	-0.061*	-0.001***	-0.001	-0.001
(9)	Dummyabpc_lowest (conservative)	0.014	0.032*	0.033	0.011	0.032*	0.033	0.001***	-0.0001	-0.0002
	Observations	16,875	13,403	11,747	16,875	13,403	11,747	15,204	13,403	11,747
Panel D Abnormal Discretionary Expenses (ABDE)										
(10)	ABDE	0.097*	0.097***	-0.017	0.098*	0.098***	-0.017	0.001*	0.003**	0.003***
(11)	Dummyabde_highest (conservative)	0.013	0.032	0.032	0.014	0.031	0.031	-0.0001	-0.0004	-0.0002
(12)	Dummyabde_lowest (aggressive)	0.011	-0.071	-0.047	0.014	-0.071	-0.047	-0.0005	-0.001	-0.0003
	Observations	5326	4113	3545	5326	4113	3545	4,741	4,113	3,545
	Industry effect fixed	yes	Yes	yes	yes	yes	yes	yes	yes	Yes
	Year effect fixed	yes	Yes	yes	yes	yes	yes	yes	yes	Yes
	Control variables	Yes	Yes	Yes	yes	yes	yes	yes	yes	Yes

* indicates statistical significance at the 10% level.
** indicates statistical significance at the 5% level.
*** indicates statistical significance at the 1% level.

In conclusion, findings from this section suggest that, in general, aggressive firms have poorer future performance than their counterparts whereas the future stock returns of conservative firms exceed their counterparts. This finding is consistent with our Hypothesis 1. Our findings also suggest that investors have different reactions towards different approaches of EM, which is consistent with the intertemporal choice theory, that current choices can lead to diverse realized outcomes in the future. However, the amount of time that investors need and when to correct manipulators' stock price are not consistent with our findings from the Univariate tests. We assume this is due to the uncontrolled factors/issues such as the endogeneity of EM indices.

Instrumental Variables and Two-Stage Least Squares Regressions

In this section, we use 2SLS regressions to control for the endogeneity of EM indicators and adopt companies' special items, R&D, and ΔPPE as instruments. The results are reported in Table 8. We expect the coefficients of DA and ABPC to be negative and that of ABCFO and ABDE to be positive. In separate regressions, we use dummy variables to represent firms from the aggressive (conservative) EM group and expect their coefficients to be negative (positive). The negative coefficient signs of aggressive EM dummies from Table 8 meet our expectations and Hypothesis 1 that after controlling for the endogeneity of EM, aggressive EM is associated with poorer long-term performance. The conservative EM dummies' positive coefficients provide evidence that conservative EM manipulators outperform their peers in the long term. We further find that endogeneity-controlled EM has better explanatory power towards firms' long-term performance than endogenous EM. For instance, the coefficients of ABDE in Table 8 are statistically more significant than that in Table 7.

In addition, the significance level of EM indicators in various periods suggests that DA and ABCFO related EM mainly affect non-financial firms' subsequent 12-month stock returns and ABPC based EM can significantly impact firms' subsequent stock performance for at least 24 months. These findings are consistent with the evidence from our Univariate analysis. The association between ABDE relevant proxies and firms' future stock returns fits our expectations that the continuous variable ABDE positively affects future stock returns, and that the aggressive (conservative) ABDE dummy negatively (positively) impacts firms' future stock performance. Our evidence also indicates that the impact significance of ABDE related proxies is not consistent among all return measures, which is consistent with our evidence from previous sections. Overall, this section suggests that investors have different reactions towards various approaches of EM, causing the impact length of different EM measures to vary.

Table 8 Two-stage Least Square regressions of earnings management and long-term stock performance

This table reports coefficients of EM proxies from Two-stage Least Square (2SLS) regressions. The dependent variable is the long-term stock performance, measured by holding period returns (HPRs), market adjusted returns (MARs) and Modigliani risk-adjusted performance (M2), respectively. The estimated period ranges from 12 months to 36 months, beginning from the year following the EM ranking (base) year. Panel A to Panel F report results based on different EM proxies, discretionary accruals, abnormal cash flow from operations, abnormal production costs and abnormal discretionary expenses, respectively. Models (1), (4), (7) and (10) use continuous variables as EM matrices; and models (2), (3), (5), (6), (8), (9), (11) and (12) use dummy variables as EM indicators. The dummy_highest is valued one if the corresponding EM measure lies in its highest quintile (Q5), zero otherwise; and the dummy_lowest is valued one if the corresponding measure lies in its lowest quintile (Q1), zero otherwise. Only dummies that represent aggressive EM are reported in each panel. Year and industry effects are fixed, and robust errors are controlled in all models. Fama-French 48-industry identification codes are applied to control for industry effects and all control variables are applied in all models.

			HPRs			MARs			M2	
	Independent variables	12 months	24 months	36 months	12 months	24 months	36 months	12 months	24 months	36 months
Panel A										
(1)	DA	-0.812**	-0.187	-0.827	-0.822**	-1.187	-0.821	-0.014**	-0.040*	-0.023**
(2)	Dummyda_highest (aggressive)	-0.073**	-0.182*	-0.106	-0.076**	-0.183*	-0.106	-0.002***	-0.006***	-0.004***
(3)	Dummyda_lowest (conservative)	0.042*	0.027	-0.041	0.043*	0.028	-0.041	0.001***	0.000	-0.001
	Observations	9,345	7,349	6,425	9,345	7,349	6,425	8,378	7,349	6,425
Panel B										
(4)	ABCFO	0.947***	1.445*	0.781	0.954***	1.445*	0.775	0.016***	0.046***	0.025**
(5)	Dummyabcfo_lowest (aggressive)	-0.136**	-0.231	-0.122	-0.140***	-0.231	-0.121	-0.003***	-0.007***	-0.003**
(6)	Dummyabcfo_ highest (conservative)	0.064**	0.060	-0.030	0.066**	0.061	-0.030	0.001***	0.001	0.000
	Observations	9,345	7,349	6,425	9,345	7,349	6,425	8,378	7,349	6,425
Panel C										
(7)	ABPC	-0.515***	-0.768**	-0.552*	-0.519***	-0.769**	-0.548*	-0.008***	-0.026***	-0.016***
(8)	Dummyabpc_highest (aggressive)	-0.090***	-0.190***	-0.191***	-0.091***	-0.191***	-0.190***	-0.001***	-0.007***	-0.005***
(9)	Dummyabpc_ lowest (conservative)	0.050***	0.084***	0.073***	0.051***	0.084***	0.072***	0.001***	0.003***	0.002***
	Observations	9,188	7,242	6,328	9,188	7,242	6,328	8,242	7,242	6,328
Panel D										
(10)	ABDE	0.331**	0.600***	0.677**	0.331**	0.600***	0.676**	0.002	0.021***	0.021***
(11)	Dummyabde_lowest (aggressive)	-0.032***	-0.058***	-0.083***	-0.031***	-0.058***	-0.082***	-0.0003	-0.002***	-0.002***
(12)	Dummyabde_ highest (conservative)	0.027***	0.000	0.004	0.027***	0.000	0.004	0.000	-0.001	-0.001**
	Observations	3,805	2,926	2,515	3,805	2,926	2,515	3,384	2,926	2,515
	Industry effect fixed	yes	yes	yes	yes	yes	yes	yes	yes	Yes
	Year effect fixed	yes	yes	yes	yes	yes	yes	yes	yes	Yes
	Control variables	Yes	Yes	Yes	yes	yes	yes	yes	yes	Yes
	Robust error	Yes	Yes	Yes	yes	yes	yes	yes	yes	Yes
	Control for endogeneity	Yes	Yes	Yes	yes	yes	yes	yes	yes	Yes

* indicates statistical significance at the 10% level.
** indicates statistical significance at the 5% level.
*** indicates statistical significance at the 1% level.

Table 9 Discretionary Accruals (DA), M-score and long-term stock performance

This table reports the univariate analysis results of long-term stock performance's mean value by DA quintiles for intentional manipulators and nonintentional firms. Panels A, B and C refer to different long-term performance measures. The estimated period ranges from 12 months to 36 months, beginning from the year following the EM ranking (base) year. The long-term performance is measured by holding period returns (HPRs), market adjusted returns (MARs), Modigliani risk-adjusted performance (M2), respectively, in each panel. DA is ranked by quintiles in each industry-year, and each industry-year has at least eight observations. Quintile 1 (Q1) firms manage earnings conservatively and Quintile 5 (Q5) firms manage earnings aggressively, based on DA measured in the base year. Q1 minus Q5 presents the difference test of the stock performance between Q1 and Q5 firms in mean; and t-test denotes the difference tests between intentional manipulators and nonintentional firms for 12-month, 24-month and 36-month periods, respectively.

		Nonintentional firms			Intentional manipulators			Nonintentional firms vs. intentional manipulators		
Quintile		12 months (1)	24 months (2)	36 months (3)	12 months (4)	24 months (5)	36 months (6)	(1)-(4)	(2)-(5)	(3)-(6)
Panel A HPRs										
Q1 (Conservative)	Mean	0.182	0.488	0.668	0.127	0.273	0.379	0.055	0.215***	0.289***
	Obs.	8,315	6,004	5,129	1,199	935	785			
Q2	Mean	0.178	0.407	0.604	0.062	0.204	0.438	0.116***	0.202***	0.167**
	Obs.	9,956	7,754	6,797	966	741	652			
Q3	Mean	0.176	0.402	0.587	0.135	0.237	0.404	0.043*	0.165***	0.183***
	Obs.	9,945	7,940	7,036	1,053	859	760			
Q4	Mean	0.163	0.349	0.541	0.109	0.337	0.528	0.054***	0.012	0.012
	Obs.	9,558	7,551	6,711	1,534	1,267	1,110			
Q5 (Aggressive)	Mean	0.156	0.338	0.464	0.104	0.222	0.427	0.052***	0.117***	0.037
	Obs.	6,192	4,740	4,198	3,835	3,073	2,721			
Q1 minus Q5		0.027	0.149***	0.204***	0.024	0.051	-0.048			
Panel B MARs										
Q1 (Conservative)	Mean	0.074	0.255	0.300	0.029	0.059	0.036	0.045	0.196***	0.264***
	Obs.	8,315	6,004	5,129	1,199	935	785			
Q2	Mean	0.070	0.175	0.240	-0.054	-0.029	0.069	0.125***	0.204***	0.170**
	Obs.	9,956	7,754	6,797	966	741	652			
Q3	Mean	0.067	0.173	0.233	0.017	0.011	0.036	0.050**	0.162***	0.197***
	Obs.	9,945	7,940	7,036	1,053	859	760			
Q4	Mean	0.056	0.122	0.186	-0.001	0.111	0.145	0.057***	0.011	0.040
	Obs.	9,558	7,551	6,711	1,534	1,267	1,110			
Q5 (Aggressive)	Mean	0.052	0.118	0.120	-0.017	-0.026	0.045	0.069***	0.144***	0.075
	Obs.	6,192	4,740	4,198	3,835	3,073	2,721			
Q1 minus Q5		0.022	0.136***	0.180***	0.046	0.085	-0.009			
Panel C M2										
Q1 (Conservative)	Mean	0.004	0.018	0.019	0.001	0.007	0.013	0.003***	0.011***	0.006***
	Obs.	7,111	6,001	5,129	1,090	935	785			
Q2	Mean	0.005	0.0166	0.0172	0.002	0.009	0.013	0.003***	0.008***	0.004***
	Obs.	8,798	7,754	6,797	865	741	652			
Q3	Mean	0.005	0.016	0.017	0.002	0.008	0.012	0.003***	0.009***	0.005***
	Obs.	8,975	7,940	7,036	969	859	760			
Q4	Mean	0.005	0.0147	0.0155	0.002	0.007	0.012	0.003***	0.008***	0.004***
	Obs.	8,579	7,550	6,711	1,439	1,267	1,110			
Q5 (Aggressive)	Mean	0.004	0.014	0.015	0.002	0.006	0.010	0.002***	0.008***	0.004***
	Obs.	5,464	4,740	4,197	3,540	3,073	2,721			
Q1 minus Q5		0.0004	0.004***	0.004***	-0.001*	0.001	0.002			

* indicates statistical significance at the 10% level.
** indicates statistical significance at the 5% level.
*** indicates statistical significance at the 1% level.

2.6.3 Estimations of Earnings Management Intentions

We use Beneish's (1999) M-scores to classify firms into two groups, firms with EM intentions (intentional manipulators) and firms without EM intentions (non-intentional firms). Intentional manipulators that engage in aggressive EM activities (AEM or REM) are expected to be actual aggressive manipulators. We perform a difference in mean analysis to explore the possibility that our original EM indicators may accidently classify a firm as an earnings manipulator.

We present the findings based on discretionary accruals (DA) in Table 9. For non-intentional firms, the differences in means of 24- and 36-month returns between conservative and aggressive firms are significantly positive at the 1% level. If M-scores can entirely detect firm' EM intentions or behaviour, no return difference should be captured between conservative and aggressive firms. Therefore, using Beneish's (1999) M-model only, to detect firms' EM activities is not suggested. As for firms that are defined as intentional manipulators, the future return differences between Q1 and Q5 groups are mostly insignificant. If DA works ideally, the future stock performance of conservative participants (Q1) are expected to surpass the future performance of aggressive participants (Q5), regardless of their EM intentions. This evidence suggests that use only DA to capture firms' EM behaviour is unadvisable.

Additionally, the mean differences of 12-, 24- and 36-month returns between non-intentional firms and intentional manipulators under all quintiles of DA are positive and mostly significant, as shown in column "(1)-(4)", "(2)-(5)" and "(3)-(6)". If using DA only, is sufficient for identifying EM behaviour, we would not expect significantly different future stock returns between intentional manipulators and non-intentional firms. Consequently, use only DA to capture firms' EM behaviour is unadvisable. On the other hand, the positive return differences between nonintentional firms and intentional manipulators fit our expectation that intentional manipulators underperform non-intentional firms in the future. The results indicate that M-scores can identify firms' EM likelihood to some extent, which means that an inclusion of M-scores could potentially improve the EM identification.

We then proceed to the analysis of the REM variables. The results based on abnormal cash flows from operations (ABCFO) are presented in Table 10. For firms with no EM intentions (refers to non-manipulators), aggressive members significantly underperform conservative ones during the subsequent 12 months at the 1% level. This indicates that when firms boost earnings via ABCFO, M-model fails in detecting their manipulation intentions, otherwise, there will be no future return difference between Q5 and Q1 for non-intentional firms. The HPR, MAR and M2 differences between Q5 and Q1 for intentional manipulators are overall statistically insignificant, suggesting that the ABCFO indicator can potentially mislead EM detection. Consistent with results from Table 9, we observe significantly positive mean differences in future returns between non-intentional firms and intentional manipulators in the majority of tests, indicating that ABCFO fails to represent EM intentions and that M-scores can help detect EM and explain future returns.

Table 10 Abnormal cash flow from operations (ABCFO), M-score and long-term stock performance

This table reports the univariate analysis results of long-term stock performance's mean value by ABCFO quintiles for intentional manipulators and nonintentional firms. Panels A, B and C refer to different long-term performance measures. The estimated period ranges from 12 months to 36 months, beginning from the year following the EM ranking (base) year. The long-term performance is measured by holding period returns (HPRs), market adjusted returns (MARs), Modigliani risk-adjusted performance (M2), respectively, in each panel. ABCFO is ranked by quintiles in each industry-year, and each industry-year has at least eight observations. Quintile 1 (Q1) firms manage earnings conservatively and Quintile 5 (Q5) firms manage earnings aggressively, based on ABCFO measured in the base year. Q1 minus Q5 presents the difference test of the stock performance between Q1 and Q5 firms in mean; and t-test denotes the difference tests between intentional manipulators and nonintentional firms for 12-months, 24-months and 36-months, respectively.

		Nonintentional firms			Intentional manipulators			Nonintentional firms vs. intentional manipulators		
Quintile		12 months (1)	24 months (2)	36 months (3)	12 months (4)	24 months (5)	36 months (6)	(1)-(4)	(2)-(5)	(3)-(6)
Panel A HPRs										
Q1 (Aggressive)	Mean	0.128	0.423	0.595	0.101	0.312	0.465	0.026	0.112*	0.130*
	Obs.	6,444	4,425	3,755	2,933	2,240	1,940			
Q2	Mean	0.167	0.413	0.586	0.094	0.260	0.484	0.073***	0.153***	0.102
	Obs.	9,012	6,768	5,880	1,612	1,271	1,116			
Q3	Mean	0.176	0.398	0.611	0.120	0.179	0.328	0.056**	0.219***	0.284***
	Obs.	9,486	7,467	6,588	1,205	997	854			
Q4	Mean	0.176	0.386	0.558	0.117	0.240	0.399	0.059***	0.146***	0.159***
	Obs.	10,098	8,089	7,203	1,204	998	890			
Q5 (Conservative)	Mean	0.199	0.381	0.544	0.108	0.196	0.454	0.091***	0.185***	0.090
	Obs.	8,966	7,268	6,468	1,651	1,381	1,238			
Q5 minus Q1		0.072***	-0.042	-0.052	0.007	-0.116	-0.011			
Panel B MARs										
Q1 (Aggressive)	Mean	0.020	0.187	0.215	-0.012	0.067	0.084	0.032	0.120**	0.132*
	Obs.	6,444	4,425	3,755	2,933	2,240	1,940			
Q2	Mean	0.060	0.183	0.225	-0.027	0.021	0.092	0.087***	0.162***	0.133**
	Obs.	9,012	6,768	5,880	1,612	1,271	1,116			
Q3	Mean	0.070	0.169	0.254	0.003	-0.058	-0.051	0.066***	0.228***	0.305***
	Obs.	9,486	7,467	6,588	1,205	997	854			
Q4	Mean	0.067	0.157	0.207	-0.001	0.006	0.033	0.068***	0.151***	0.174***
	Obs.	10,098	8,089	7,203	1,204	998	890			
Q5 (Conservative)	Mean	0.094	0.158	0.196	0.003	-0.018	0.106	0.090***	0.176***	0.090
	Obs.	8,966	7,268	6,468	1,651	1,381	1,238			
Q5 minus Q1		0.074***	-0.029	-0.019	0.015	-0.085	0.022			
Panel C M2										
Q1 (Aggressive)	Mean	0.002	0.016	0.017	0.001	0.007	0.011	0.001***	0.009***	0.006***
	Obs.	5,389	4,424	3,755	2,671	2,240	1,940			
Q2	Mean	0.004	0.016	0.017	0.001	0.008	0.013	0.003***	0.009***	0.004***
	Obs.	7,897	6,767	5,880	1,468	1,271	1,116			
Q3	Mean	0.005	0.016	0.017	0.002	0.006	0.010	0.003***	0.010***	0.006***
	Obs.	8,513	7,467	6,588	1,112	997	854			
Q4	Mean	0.005	0.016	0.016	0.003	0.009	0.012	0.002***	0.007***	0.004***
	Obs.	9,086	8,088	7,202	1,116	998	890			
Q5 (Conservative)	Mean	0.005	0.016	0.016	0.002	0.006	0.011	0.003***	0.010***	0.005***
	Obs.	8,072	7,267	6,468	1,550	1,381	1,238			
Q5 minus Q1		0.003***	0.0004	-0.002	0.001*	-0.0003	-0.0002			

* indicates statistical significance at the 10% level.
** indicates statistical significance at the 5% level.
*** indicates statistical significance at the 1% level.

Table 11 Abnormal production costs (ABPC), M-score and long-term stock performance

This table reports the univariate analysis results of long-term stock performance's mean value by ABPC quintiles for intentional manipulators and nonintentional firms. Panels A, B and C refer to different long-term performance measures. The estimated period ranges from 12 months to 36 months, beginning from the year following the EM ranking (base) year. The long-term performance is measured by holding period returns (HPRs), market adjusted returns (MARs), Modigliani risk-adjusted performance (M2), respectively, in each panel. ABPC is ranked by quintiles in each industry-year, and each industry-year has at least eight observations. Quintile 1 (Q1) firms manage earnings conservatively and Quintile 5 (Q5) firms manage earnings aggressively, based on ABPC measured in the base year. Q1 minus Q5 presents the difference test of the stock performance between Q1 and Q5 firms in mean; and t-test denotes the difference tests between intentional manipulators and nonintentional firms for 12-month, 24-month and 36-month periods, respectively.

		Nonintentional firms			Intentional manipulators			Nonintentional firms vs. intentional manipulators		
Quintile		12 months (1)	24 months (2)	36 months (3)	12 months (4)	24 months (5)	36 months (6)	(1)-(4)	(2)-(5)	(3)-(6)
Panel A HPRs										
Q1 (Conservative)	Mean	0.193	0.408	0.561	0.133	0.256	0.466	0.060***	0.152***	0.095
	Obs.	8,662	6,780	5,989	1,846	1,492	1,305			
Q2	Mean	0.188	0.411	0.596	0.153	0.391	0.511	0.036	0.020	0..086
	Obs.	9,182	7,196	6,353	1,341	1,073	945			
Q3	Mean	0.172	0.410	0.643	0.123	0.241	0.504	0.049*	0.169***	0.139*
	Obs.	8,856	6,797	5,968	1,302	1,004	885			
Q4	Mean	0.159	0.384	0.532	0.108	0.186	0.301	0.051*	0.198***	0.232***
	Obs.	8,033	6,147	5,436	1,192	942	817			
Q5 (Aggressive)	Mean	0.151	0.393	0.545	0.101	0.296	0.466	0.051**	0.098*	0.079
	Obs.	6,608	4,997	4,370	1,646	1,292	1,146			
Q1 minus Q5		0.042***	0.014	0.016	0.033	-0.040	-0.0003			
Panel B MARs										
Q1 (Conservative)	Mean	0.084	0.178	0.207	0.026	0.040	0.121	0.058***	0.138***	0.085
	Obs.	8,662	6,780	5,989	1,846	1,492	1,305			
Q2	Mean	0.084	0.187	0.245	0.033	0.160	0.153	0.050*	0.028	0.092
	Obs.	9,182	7,196	6,353	1,341	1,073	945			
Q3	Mean	0.066	0.183	0.288	0.0104	0.0101	0.140	0.056**	0.173***	0.149*
	Obs.	8,856	6,797	5,968	1,302	1,004	885			
Q4	Mean	0.052	0.156	0.175	-0.013	-0.057	-0.081	0.065**	0.213***	0.257***
	Obs.	8,033	6,147	5,436	1,192	942	817			
Q5 (Aggressive)	Mean	0.041	0.159	0.182	-0.015	0.061	0.089	0.056**	0.098*	0.093
	Obs.	6,608	4,997	4,370	1,646	1,292	1,146			
Q1 minus Q5		0.043***	0.019	0.025	0.041	-0.021	0.033			
Panel E M2										
Q1 (Conservative)	Mean	0.005	0.017	0.016	0.003	0.008	0.012	0.002***	0.008***	0.004***
	Obs.	7,712	6,779	5,988	1,708	1,492	1,305			
Q2	Mean	0.005	0.017	0.017	0.003	0.012	0.015	0.002***	0.005***	0.002*
	Obs.	8,195	7,195	6,353	1,221	1,073	945			
Q3	Mean	0.005	0.017	0.017	0.002	0.009	0.013	0.003***	0.008***	0.004***
	Obs.	7,818	6,795	5,968	1,175	1,004	885			
Q4	Mean	0.004	0.016	0.016	0.001	0.006	0.010	0.003***	0.009***	0.006***
	Obs.	7,107	6,147	5,436	1,085	942	817			
Q5 (Aggressive)	Mean	0.004	0.015	0.017	0.002	0.008	0.012	0.002***	0.008***	0.005***
	Obs.	5,777	4,997	4,370	1,505	1,292	1,146			
Q1 minus Q5		0.001***	0.001	-0.0004	0.002***	0.001	0.0004			

* indicates statistical significance at the 10% level.
** indicates statistical significance at the 5% level.
*** indicates statistical significance at the 1% level.

Table 12 Abnormal discretionary expenses (ABDE), M-score and long-term stock performance

This table reports the univariate analysis results of long-term stock performance's mean value by ABDE quintiles for intentional manipulators and nonintentional firms. Panels A, B and C refer to different long-term performance measures. The estimated period ranges from 12 months to 36 months, beginning from the year following the EM ranking (base) year. The long-term performance is measured by holding period returns (HPRs), market adjusted returns (MARs), Modigliani risk-adjusted performance (M2), respectively, in each panel. ABDE is ranked by quintiles in each industry-year, and each industry-year has at least eight observations. Quintile 1 (Q1) firms manage earnings conservatively and Quintile 5 (Q5) firms manage earnings aggressively, based on ABDE measured in the base year. Q1 minus Q5 presents the difference test of the stock performance between Q1 and Q5 firms in mean; and t-test denotes the difference tests between intentional manipulators and nonintentional firms for 12-month, 24-month and 36-month periods, respectively.

		Nonintentional firms			Intentional manipulators			Nonintentional firms vs. intentional manipulators		
Quintile		12 months (1)	24 months (2)	36 months (3)	12 months (4)	24 months (5)	36 months (6)	(1)-(4)	(2)-(5)	(3)-(6)
Panel A HPRs										
Q1 (Conservative)	Mean	0.179	0.436	0.576	0.020	0.012	0.020	0.159***	0.424***	0.380***
	Obs.	2318	1769	1545	372	296	256			
Q2	Mean	0.172	0.385	0.550	0.099	0.256	0.564	0.074*	0.129	-0.015
	Obs.	2790	2161	1899	403	326	292			
Q3	Mean	0.166	0.389	0.570	0.075	0.147	0.274	0.091**	0.242***	0.296**
	Obs.	2733	2069	1799	403	339	296			
Q4	Mean	0.170	0.361	0.571	0.129	0.353	0.471	0.041	0.007	0.099
	Obs.	2761	2098	1802	505	401	347			
Q5 (Aggressive)	Mean	0.199	0.480	0.657	0.122	0.204	0.364	0.077*	0.276***	0.293**
	Obs.	2211	1678	1450	736	572	499			
Q5 minus Q1		0.020	0.044	0.081	0.102*	0.192*	0.168			
Panel B MARs										
Q1 (Conservative)	Mean	0.081	0.218	0.242	-0.068	-0.156	-0.099	0.149***	0.374***	0.341***
	Obs.	2318	1769	1545	372	296	256			
Q2	Mean	0.076	0.176	0.221	-0.001	0.073	0.237	0.078*	0.102	-0.016
	Obs.	2790	2161	1899	403	326	292			
Q3	Mean	0.071	0.188	0.245	-0.025	-0.069	-0.072	0.097**	0.257***	0.317**
	Obs.	2733	2069	1799	403	339	296			
Q4	Mean	0.075	0.149	0.233	0.047	0.185	0.180	0.028	-0.036	0.054
	Obs.	2761	2098	1802	505	401	347			
Q5 (Aggressive)	Mean	0.105	0.271	0.329	0.040	0.039	0.090	0.065*	0.233***	0.239**
	Obs.	2211	1678	1450	736	572	499			
Q5 minus Q1		0.024	0.053	0.086	0.108*	0.195*	0.188			
Panel E M2										
Q1 (Conservative)	Mean	0.004	0.018	0.0177	-0.001	-0.002	0.007	0.006***	0.020***	0.011***
	Obs.	2042	1769	1545	341	296	256			
Q2	Mean	0.005	0.017	0.017	0.002	0.007	0.011	0.003***	0.010***	0.005***
	Obs.	2457	2161	1899	377	326	292			
Q3	Mean	0.005	0.016	0.017	0.002	0.006	0.007	0.003***	0.011***	0.010***
	Obs.	2388	2069	1799	375	339	296			
Q4	Mean	0.004	0.015	0.016	0.002	0.011	0.013	0.002***	0.004	0.003
	Obs.	2434	2097	1802	458	401	347			
Q5 (Aggressive)	Mean	0.004	0.018	0.018	0.002	0.005	0.011	0.002**	0.013***	0.007***
	Obs.	1946	1677	1450	680	572	499			
Q5 minus Q1		-0.0001	-0.0004	-0.0001	0.004***	0.007*	0.004			

* indicate statistical significance at the 10% level.
** indicate statistical significance at the 5% level.
*** indicate statistical significance at the 1% level.

Next, we present the results from abnormal production costs (ABPC) in Table 11. The results based on ABPC are incredibly similar with results based on ABCFO. As for non-intentional firms, aggressive manipulators significantly underperform conservative ones measured by the subsequent 12-month HPRs (0.042), MARs (0.043) and M2 (0.001). The results indicate that when firms use ABPC to boost earnings, M-model can hardly fully detect firms' EM likelihood. As for intentional manipulators, the return differences between Q5 and Q1 are, in general, statistically insignificant, suggesting that ABPC could mislead the identification of EM. We also find that the future return differences between non-intentional firms and intentional manipulators of all types of stock returns and at all quintiles of ABPC are positive and mostly significant. The results denote that ABPC may fail to explain integral EM behaviour and that considering EM intentions while detecting EM behaviour is advisable.

Finally, we present the results based on abnormal discretionary expenses (ABDE) in Table 12. No significant differences in means are observed between conservative and aggressive non-intentional firms, which implies firms classified as aggressive firms may have no intention to manipulate earnings (i.e. aggressive firms could be classified as earnings manipulators by chance). Therefore, ABDE could mislead the detection of EM behaviour. On the other hand, 12- and 24-month return differences between conservative and aggressive intentional-manipulators are significantly positive at the 10% level or better, indicating that the M-scores can rarely fully detect ABDE-based EM activities. Moreover, the majority of future return differences between non-intentional firms and intentional manipulators are significantly positive, suggesting that ABDE may fail to explain integral EM behaviour and that considering M-scores while detecting EM behaviour is advisable.

In summary, our findings from univariate tests in this section suggest that AEM and REM measures may mislead EM detection and that EM intentions can hardly represent all EM likelihood, which is consistent with our Hypothesis 2. As a result, we suggest interacting AEM and REM indicators with M-scores, respectively, to compressively and effectively detect firms' EM behaviour.

We then interact the M-score dummy (M-dummy) with aggressive AEM and REM dummies, respectively, in our baseline OLS models (equation (13)) and 2SLS models (equations (15) and (16)). The interaction aims to reduce the possibility that a firm is wrongly classified as an income-increasing earnings manipulator by AEM or REM indicators. Beneish's (1999) M-model can detect income-increasing EM behaviour but fail to capture income-decreasing EM activities. Firms that are classified as non-intentional participants by the M-model comprise income-decreasing earnings manipulators and firms that are not manage earnings. Therefore, we do not interact the conservative EM dummies with the M-dummy.

Table 13 Earnings management, M-score and long-term performances

This table reports coefficients of interacted EM and M-dummy proxies from Ordinary Least Square (OLS) (odd numbered) and Two-stage Least Square (2SLS) (even numbered) regressions. The dependent variable is the long-term stock performance, measured by holding period returns (HPRs), market adjusted returns (MARs) and Modigliani risk-adjusted performance (M2), respectively. The estimated period ranges from 12 months to 36 months, beginning from the year following the EM ranking (base) year. Panel A to Panel D report results based on different EM proxies, i.e., discretionary accruals, abnormal free cash flow from operations, abnormal production costs and abnormal discretionary expenses, respectively. Models (1), (3), (5) and (7) apply OLS estimations and models (2), (4), (6) and (8) apply 2SLS estimations. All models use interacted aggressive EM dummies and M-dummy as explanatory variables. The dummy_highest is valued one if the corresponding EM measure lies in its highest quintile (Q5), zero otherwise; and the dummy_lowest is valued one if the corresponding measure lies in its lowest quintile (Q1), zero otherwise. Year and industry effects are fixed, and the robust errors are used in all the models. Fama-French 48-industry identification codes are used to control for industry effects and all control variables are applied in all models.

		HPRs			MARs			M2		
	Independent variables	12 months	24 months	36 months	12 months	24 months	36 months	12 months	24 months	36 months
Panel A Discretionary Accruals (DA)										
(1)	Dummyda_highest*M-dummy (Not control for endogeneity)	-0.076***	-0.087*	-0.146**	-0.076***	-0.087*	-0.146**	-0.003***	-0.004**	-0.004***
	Observations	12,122	9,222	7,910	12,122	9,222	7,910	10,693	9,222	7,910
(2)	Dummyda_highest* M-dummy (Control for endogeneity)	-0.077*	-0.422***	-0.413***	-0.080*	-0.422***	-0.413***	-0.003***	-0.016***	-0.013***
	Observations	9,346	7,343	6,419	9,346	7,343	6,419	8,379	7,343	6,419
Panel B Abnormal Cash Flow from Operations (ABCFO)										
(3)	Dummyabcfo_lowest* M-dummy (Not control for endogeneity)	-0.086	-0.131*	-0.091	-0.084	-0.131*	-0.091	-0.003**	-0.005**	-0.004**
	Observations	12,124	9,223	7,910	12,124	9,223	7,910	10,695	9,223	7,910
(4)	Dummyabcfo_lowest* M-dummy (Control for endogeneity)	-0.064**	-0.140*	-0.068	-0.067**	-0.140*	-0.068	-0.001***	-0.005***	-0.003***
	Observations	9,346	7,343	6,419	9,346	7,343	6,419	8,379	7,343	6,419
Panel C Abnormal Production Costs (ABPC)										
(5)	Dummyabpc_highest* M-dummy (Not control for endogeneity)	-0.121**	-0.166**	-0.043	-0.118**	-0.167**	-0.044	-0.002**	-0.004	-0.001
	Observations	11,545	8,841	7,582	11,545	8,841	7,582	10,227	8,841	7,582
(6)	Dummyabpc_highest* M-dummy (Control for endogeneity)	-0.099***	-0.296***	-0.329***	-0.100***	-0.296***	-0.327***	-0.002***	-0.012***	-0.010***
	Observations	9,346	7,343	6,419	9,346	7,343	6,419	8,379	7,343	6,419
Panel D Abnormal Discretionary Expenses (ABDE)										
(7)	Dummyabde_lowest* M-dummy (Not control for endogeneity)	-0.093	-0.190*	-0.300*	-0.088	-0.189*	-0.299*	-0.003**	-0.002	-0.006
	Observations	4,037	3,024	2,556	4,037	3,024	2,556	3,544	3,024	2,556
(8)	Dummyabde_lowest* M-dummy (Control for endogeneity)	-0.048***	-0.043**	-0.062*	-0.047***	-0.044**	-0.061*	-0.0004	-0.001	-0.0002
	Observations	9,346	7,343	6,419	9,346	7,343	6,419	8,379	7,343	6,419
	Industry effect fixed	yes	yes	yes	yes	yes	yes	yes	yes	yes
	Year effect fixed	yes	yes	yes	yes	yes	yes	yes	yes	yes
	Robust errors	yes	yes	yes	yes	yes	yes	yes	yes	yes
	Control variables	yes	yes	yes	yes	yes	yes	yes	yes	yes

* indicates statistical significance at the 10% level.
** indicates statistical significance at the 5% level.
*** indicates statistical significance at the 1% level.

We present the regression results in Table 13. The coefficients of the interactions are negative and generally significant, suggesting that the more a firm manipulate earnings upwards, the lower is the subsequent stock returns. Additionally, in general, the explanation power of the interactions on future stock performance is greater than that of individual EM indicators (i.e. Dummyda_highest, Dummyabcfo_lowest, Dummyabpc_highest and Dummyabde_lowest) in both OLS and 2SLS regressions. For instance, the coefficients of Dummyda_highest on 12-, 24- and 36-month HPRs in OLS regressions are -0.030, -0.062 and -0.073 [5], respectively, whereas the coefficients of the interaction (i.e. Dummyda_highest*M-dummy) are -0.076, -0.087 and -0.146[6], respectively. The results are consistent with our Hypothesis 3 that M-scores help to improve the prediction power of EM approaches on future stock performance.

In an efficient market, future stock returns should not be affected by firms' EM activities in previous periods, because stock prices from the current period should fully capture firms' manipulation behaviour. Our findings, therefore, suggest that the market is inefficient which makes it difficult for investors to effectively and sufficiently detect firms' EM practices.

2.6.4 Additional Robustness Checks

The effects of delisting – Over the sample period, 1,825 out of 20,532 observations do not appear the year following portfolio formation in the highest quintile of discretionary accruals (DA). This amounts to a delisting ratio of 9%. Out of the 91,498 entries in the remainder quintiles based on DA, 8,186 entries disappear from the sample in the year following the year of the portfolio construction. This also approximates to a delisting ratio of 9%. The delisting rate of aggressive REM firms is also close to the rate of their counterparts. The delisting ratio of manipulators and their peers appear to track each other closely, therefore, we do not believe that delisting firms are driving our results.

Additional measures of risk-adjusted returns – Our previous analyses suggest that risk-adjusted returns (i.e. M2) is negative affected by firms' previous year's EM and that M-scores can help AEM and REM to better predict firms' future risk-adjusted returns. To check the robustness of these findings, we repeat the analysis using additional risk-adjusted return measures, Sharpe (1994) ratio and Jensen (1968) alpha. The results are shown in Appendix AII, where the coefficients of EM indicators are mostly negative. This is consistent with the finding obtained from previous sections that aggressive EM has a

[5] The results from OLS regressions can be found in Table 7 model (2).

[6] The results can be found in Table13 model (1).

negative impact on firms' long-term risk-adjusted returns. Comparing the coefficients of the individual EM indicators and the interactions, our evidence also suggests that interactions have better explanatory power towards future returns than individual EM measures.

Reverse causality – We test the effects of current year's EM on subsequent stock returns. However, the causal association between EM and stock performance can be both ways, i.e., poor stock performance could force managers to implement short-term fixes to arrest the decline in share performance and to improve investors' perceptions of the firm. As a result, we mitigate this possibility in the analyses by regressing future (i.e., year t+1) EM variables on base year's stock performance, EM proxies, special items, nature logarithm of research and development expenditure (Log(R&D)), and changes in value of property, plant and equipment (ΔPPE). [7] Our results, reported in Appendix AIII, show that the coefficients of stock returns are mostly positive and even significant in some cases, suggesting that the detrimental effect of EM on stock prices is not caused by the reverse effect. In other words, our previous finding that aggressive EM firms subsequently underperform their counterparts is robust from reverse causality.

Falsification tests – Our previous evidence proves firms that manipulate earnings aggressively experience poor future stock performance. However, these results can be induced by the possibility that aggressive firms normally underperform their peers. To address this concern, we investigate whether aggressive EM firms also have poor stock returns at the same period by regressing stock returns on EM interactions at time t. All the control variables are considered and the results are reported in Appendix AIV. If the adverse impact of EM on future stock performance is caused by the overall negative association between EM and stock returns, we should observe significantly negative coefficients on EM proxies in Appendix AIV. The coefficients of EM indices are overall positive and some of them are significant at the 10% level, which is inconsistent with the overall negative association explanation, suggesting the robustness of our previous findings.

Fiscal and Calendar year re-match – Our chapter roughly matches fiscal-year data from the COMPUSTAT database with calendar-year data from the CRSP database due to the reasons mentioned previously. This section is conducted to study whether the simple match that we adopt is driving our findings by accurately adjusting stock returns to annual returns based on the fiscal year for each firm. A concern of using this type of pairing approach is

---

[7] Special items, nature logarithm of research and development expenditure (Log(R&D)), and changes in value of property, plant and equipment (ΔPPE) are also used as instruments for EM in equation (15).

that firms often have identical fiscal/accounting years, which makes it hard when comparing their stock returns. We report baseline regression results of stock returns that are generated using fiscal years in Appendix AV. The results are consistent with that in Table 7 and Table 13, suggesting that our findings are not sensitive to data matching methods.

Quantile impacts – We then conduct Shapiro Wilk tests. Our results indicate that variables of stock returns do not perfectly fit normal distributions. Therefore, in this section, we apply quantile regressions to provide a better view towards the association between EM and future stock returns. Using interacted EM and M-dummy as our main variable of interest, we conduct unconditional quantile regressions suggested by Borgen (2018). We specifically estimated 10th quantile, 50th quantile and 90th quantile of the future stock performance, controlling for firm-fixed effects and year-fixed effects in all models. We report results in Appendix AVI. The results are consistent with our previous finding that aggressive earnings manipulators have relatively lower future performance than their counterparts. Our evidence also suggests that aggressive manipulators that use DA, ABCFO and ABPC to boost earnings, underperform their peers especially for firms at a lower quantile of stock returns, whereas ABDE-based aggressive manipulators underperform their peers especially for firms belonging to a higher quantile of the future returns.

2.7 Conclusions

This chapter tests the unconditional effects of both AEM and REM on firms' subsequent stock performance and the effectiveness of the impacts based on a sample of 9,859 US public corporations from 1990 to 2016. The results are unequivocal, i.e. both discretionary accruals and real activities manipulation adversely affect subsequent stock performance under ordinary settings. To the extent that EM adds to the uncertainty in share valuations, it does not, however, compensate investors accordingly. Our study further documents that investors' reactions towards different EM approaches are diverse, therefore, price correction occurs at different future periods for earnings manipulators that use different EM methods. Our evidence suggests that accruals and operational cash flow based EM activities mainly affect firms' subsequent 12-month returns and production costs based EM practices can influence firms' future stock performance for around 24 months. Our findings support the inefficient market theory and imply that firm managers could potentially choose EM approaches based on their future stock price expectations and investors' potential reactions.

Additionally, we find that investors and regulators who use AEM, REM and M-scores individually to capture EM behaviour, are potentially misled. Consequently, the interacted

EM indicators suggested in this chapter are designed to assist investors and regulators to identify earnings manipulators more rationally and explicitly. As a result, our approach possesses better practice-oriented value to investors and investment managers. Our findings would also assist researchers in establishing the true and certain effects of EM on investors' wealth. Additionally, our findings suggest investors consider using a combined measure of EM behaviour and EM intentions to capture firms' EM activities and for making better investment decisions.

Admittedly, the identification problem of EM intentions stays in the line of this research. We use M-scores in this chapter to evaluate firms' earnings management intentions. However, the indices that are used to build the M-scores contain not only proxies to capture firms' EM intentions but indicators to roughly detect firms' EM practices. This chapter has not free the impact of EM detections from the M-scores due to the difficulty in restructuring the formula and allocating new weights to the indices. Therefore, using M-scores to fully represent firms' EM intentions requires further discussion.

Moving forwards, there are several open fronts for academic research to consider. First, generating a clean EM intention index would help improve the explanatory power of EM indices on subsequent stock performance. The measure of EM intentions can be further improved in future studies by generating a new index incorporating only factors that are likely to drive firms' EM intentions. The factors could comprise but are not limited to sale changes, gross margin changes, leverage changes, peer performance difference changes, auditor changes and board member specifications.

Finally, this chapter has treated firms from different states of U.S. identically. However, it may be of investors' interests to know whether the association between EM and future stock performance would differ based on firms' locations due to various regulations at the state level. Consequently, future studies could also consider examining whether firm location could diverse the impact of EM on financial and non-financial firms' subsequent performance.

Chapter 3 Informational Role of Accounting Managerial Behaviour in the U.S. Banking Industry

3.1 Introduction

This chapter studies the impact of accounting managerial behaviour (AMB) on future bank performance, where AMB is generated by interacting banks' earnings management (EM) indicators with their bank efficiency (BE) matrix or managerial behaviour (MA) index. A high level of (superior) AMB is defined as a combination of a low level of EM and a high level of BE (or MA), whilst a low level of (poor) AMB is a combination of a high level of EM and a low level of BE (or MA).

Prior studies have investigated the purposes, incentives and consequences of banks' EM practices (see e.g. Beatty, Ke, Petroni and Beatty, 2002; Cornett, McNutt and Tehran, 2009; Cheng, Warfield and Ye, 2011; Cohen, Cornett, Marcus and Tehranian, 2014). However, the empirical evidence towards the signalling power of EM on bank performance is controversial. Ahmed, Takeda and Thomas (1998) suggest that EM has a positive impact on bank performance; Wahlen (1994) suggests that there exists a negative impact; whereas Beaver and Engel (1996) document no impact between the two.

The mixed association found between EM and future bank performance could be due to the sensitivity of EM's signalling power from empirical model specifications and research designs (Lobo and Yang, 2001). This chapter is initiated to provide further evidence to the association. Additionally, there may exist uncontrolled factors in previous studies that could affect banks' EM practices, causing an unstable signalling effect on future bank performance. This study attempts to address the issue by introducing additional factors that could potentially stabilize the signalling impact. We choose BE and MA as additional factors, where BE is banks' ability of generating revenues per resource whilst MA is bank managers' ability to generate additional BE.

EM behaviour is predominately driven by the differences between banks' revenue targets and their realised revenues. Efficient banks are expected to generate more revenues per unit of resource. Therefore, efficient banks are less likely to engage in aggressive EM than inefficient ones, when those banks have similar amount of resources. However, when efficient banks have a lower amount of resources than inefficient ones, they could still engage in aggressive EM to artificially increase their earnings. In this case, it is hard to signal banks' future performance using only EM or BE indicators, because they are likely to have opposite impacts on future bank performance. To address this concern, we suggest to interact EM and BE proxies to stabilize the signalling effects of EM and BE on future bank performance.

Banks that have able managers are expected to manage resources better and consequently generate more revenues than banks that have unable managers. Therefore, banks with able managers are less likely to engage in aggressive EM than their counterparts, when those banks have similar amount of resources. However, similar as the association between EM and BE, when banks with able managers have a very low amount of resources, they could still engage in aggressive EM to artificially manipulate their earnings upwards. In this case, it is hard to signal banks' future performance using only EM or MA indicators, because they are likely to have adverse effects on banks' future performance. Consequently, we suggest to interact EM and MA indexes to stabilize the signalling role of EM and MA on future bank performance.

Banks conduct income-increasing earnings management by overstating earnings, which may cause a side effect on their reputation, whereas bank reputation is important for attracting potential depositors. Therefore, we expect banks that engage in income-increasing EM to have poorer performance in the next fiscal year than other banks. In contrast, banks conduct income-decreasing earnings management by smoothing earnings. Smoothing earnings is interpreted as a strengthened signal of future performance, even though it eliminates current earnings (Wahlen, 1994; Beaver, Eger, Ryan and Wolfson, 1989). Therefore, we expect banks that engage in income-decreasing EM to outperform their peers in the next fiscal year.

Efficient banks are found to retain more capital, have less risk-weighted assets, but take more credit risks than inefficient banks (Ding and Sickles, 2018), thus they are likely to outperform their peers in the future. Able managers work more efficiently than relatively incapable managers, they are more likely to make better decisions and select sustainable projects that could potentially contribute to better operating performance in the near future. Therefore, we expect efficient (inefficient) banks with income-decreasing (income-increasing) EM behaviour to have a better (worse) future performance than other banks. In addition, we expect banks that have able (unable) managers who conduct income-decreasing (income-increasing) EM practices to outperform (underperform) their peers subsequently.

We test the relationship between AMB and future bank performance using a sample of 589 local commercial banks in the United States from 1998 to 2017. Our evidence supports our hypotheses that banks with superior AMB outperform other banks, while banks with poor AMB underperform their peer banks in the next fiscal year. These findings indicate that banks with high efficiency (or high managerial ability) as well as conducting income-decreasing EM, perform better than their peers in the next fiscal year, whereas banks with low efficiency (or low managerial ability) and at the same time of conducting income-increasing EM, perform worse than their peers in the following year. Further tests show that our findings are robust even after considering business-cycle effects, Sarbanes-Oxley Act (SOX) implementation, global financial crisis (GFC) effects, self-selection bias, sample selection bias, dynamic impacts and endogenous issues. Overall, we offer strong evidence suggesting that banks' AMB can explain their future performance.

Next, we investigate the importance and the power of AMB in explaining future bank performance by interacting AMB indicators with bank size. Previous studies have documented a positive association between bank size and bank performance (see Köster and Pelster, 2017; Meles, Porzio, Sampagnaro and Verdoliva, 2016; Mamatzakis and Bermpei, 2016; Bakoush, Abouarab and Wolfe, 2018). After introducing AMB into the association between bank size and bank performance, we find that the relationship varies. Our evidence shows that bank size has a positive impact on future bank performance of superior AMB banks, whilst the size of banks negatively affects poor AMB banks' future performance. These findings suggest that AMB potentially dominate the size effect on bank performance.

This chapter contributes to the existing literature in three ways. First, it is the first to suggest signalling future bank performance using AMB indicators. We also suggest to stabilize the impact of EM and BE (or MA) on future bank performance by mainly focusing on typical groups of banks (i.e. superior AMB banks and poor AMB banks). Our evidence indicates that when banks are efficient enough to generate more revenue per resource than their peers, and their revenue needs to be smoothed to reach their income targets, then these banks are most likely to outperform their peers in the next fiscal year. In contrast, for banks that generate less revenue per resource than their peers, and are also required to artificially increase their earnings to achieve financial targets, then they are most likely to underperform their peers subsequently. Therefore, our results highlight the association between AMB and future bank performance as well as highlighting the importance of AMB in the banking studies.

Second, this chapter adds to the literature of data transformation (see e.g. Butler, Connor and Kieschnick, 2014; Marks and Musumeci, 2017; Bergbrant and Hunter, 2018 and Gupta, Mallick and Mishra, 2018). We propose a transformation, based on the cost function of the logistic regression, to formalize the original MA value. This transformation is expected to provide a more reasonable economic meaning to the MA indicator. Our transformation formula can also be widely used to formalize other variables with similar purposes as our transformation of MA. Compared with transformations that use maximum and minimum values to standardize the initial value and range it within a desired threshold, our method is able to assign the initial mean value with a specific value (i.e. 0.5) among diverse groups and simultaneously limit the new value between 0 and 1 after the transformation.

Finally, this chapter adds to the existing literature regarding the size effect of banks. Previous literature has documented that the impact of bank size on market to book value differs for large and small bank (Gianni, 2001); bank size adversely affects banks' net return on small business lending (Carter and Mcnulty, 2005 and Berger, Miller, Petersen, Rajan and Stein, 2005); and that larger banks are more likely to receive government bailouts (Davila and Walther, 2019), etc. Our study adds to the literature by showing that the impact of bank size on future bank performance may also rely on banks' accounting managerial behaviour. Our finding sheds light on the impact of banks' managerial behaviour on size effect among commercial banks and highlights the importance of AMB in commercial banking studies.

The rest of the chapter is organised as follows. Section 3.2 discusses the background of earnings management. Section 3.3 performs a literature review. Section 3.4 documents our main hypotheses. Section 3.5 presents the data and main variables generation. Section 3.6 discusses the empirical analysis design. Section 3.7 reports our empirical results and discussions. Section 3.8 summarizes and concludes the chapter.

3.2 Background of EM in the U.S. banking industry

Loan loss provisions (LLPs) reflect banks' assessment towards potential or expected default loan portions (Cohen, Cornett, Marcus and Tehranian, 2014). The baseline recognition and measurement of LLPs are specified in Statement of Financial Accounting Standards (SFAS) No.5, as well as SFAS No. 114 (El Sood, 2012). LLPs are initially generated to help banks eliminate credit risks, however, they have also been found to be one of the banks' EM approaches (Beatty, Ke, Petroni and Beatty, 2002). An LLR is accumulated LLPs over time, and is also treated as an EM indicator. Similar to LLPs, a high level of LLRs prevent banks from failing from unexpected loan losses. LLRs that are below expected value indicate an understatement of loan losses (Cohen, Cornett, Marcus and Tehranian, 2014).

Banks also adjust earnings by artificially trading investment securities, which is captured by the discretion in realised security gains and losses (Beatty, 1998; Barth, Gomez-Biscarri, Kasznik and López-Espinosa, 2017; Cohen, Cornett, Marcus and Tehranian, 2014). Compared with the use of LLPs and LLRs, the use of security gains and losses is less audited and regulated (Cohen, Cornett, Marcus and Tehranian, 2014). Therefore, using the latter method to manage earnings is relatively unlikely to be captured by investors, regulators and auditors compared with the method based on LLPs and LLRs.

Regulators have been aware that controlling banks' EM activities assists generating a more transparent and effective banking industry. After the massive losses in banks' loan portfolios during the global financial crisis (2007), more attention has been given to the default risks in the banking industry (El Sood, 2012). Accordingly, accounting standards such as SFAS No. 157 was published in November 2007 to strengthen the scrutiny of banks' EM behaviour via manipulating gains and losses in the securities (Cohen, Cornett, Marcus and Tehranian, 2014). Since then, artificially realising security gains and losses are less used by bank managers to achieve their earnings targets (Cohen, Cornett, Marcus and Tehranian, 2014). Our sample applies to the period from 1998 to 2017. Our results could be affected by the implementation of the SFA No. 157 if we adopt the measure of discretionary realised security gains and losses. Therefore, we do not use the discretionary realised gains and losses in the securities as a measure of earnings management, to achieve a consistent impact of EM in our sample.

Banks have diverse motives of manipulating earnings. Beatty, Ke, Petroni and Beatty (2002) document that public banks have a higher preference of stabilizing earnings than private banks, therefore, they are more likely to avoid small earnings losses by manipulating LLPs and security gains and losses. Kanagaretnam, Lobo and Mathieu (2004) document that banks smooth earnings to reduce the cost of capital and to boost stock prices. Cornett, McNutt and Tehran (2009) find that managers manipulate earnings less when manipulation incentives and opportunities are limited. They find that banks with lower earnings before extraordinary items and taxes manage earnings more; bank CEOs whose compensation are more sensitive to bank performance manage earnings more; and that banks with a more independent board manage earnings less. They further find that banks with lower capital adequacy manipulate earnings less, because conduct activities to improve capital adequacy diverts bank managers' attention from managing earnings.

Cheng, Warfield and Ye (2011) find that bank managers who have high equity incentives, measured by the sum of option grants, exercisable options, un-exercisable options and stocks owned by CEOs, manage earnings more than other bank managers. However, this finding stands only when capital ratios are about to hit the required minimum level. The finding indicates that bank managers manipulate earnings to increase their own benefits. Alali and Jaggi (2011) find that banks are more likely to manage earnings if their asset portfolios contain high risks. They find that banks engaged in more EM activities during the global financial crisis period. Similarly to Alali and Jaggi (2011), El Sood (2012) finds that banks extensively use LLPs to artificially boost earnings during the economic recessions.

The author further documents that banks smooth earnings by artificially decreasing LLPs, and that banks tend to smooth earnings when they achieve exceed profits. Banks are also found to manipulate earnings downwards during the non-recessionary periods, or when banks successfully hit the regulatory minimum capital ratio acquired by the Federal Deposit Insurance Corporation (FDIC).

Recently, Barth, Gomez-Biscarri, Kasznik and López-Espinosa (2017) find that banks with positive earnings engage in income-decreasing EM, while banks with negative earnings artificially boost earnings. They also find that regulatory capital constrains income-increasing EM activities. Dong and Zhang (2018) find that banks manipulate earnings to meet or beat benchmarks. They also find that banks manipulate earnings more when the disclosure location of the EM indicators is less emphasised in the income statement. For instance, banks that disclose unrealised gains and losses immediately after the net income value or in an outstanding file attaching to the income statement are less likely to manage earnings.

Prior studies also document that high-quality auditors pressure banks to provide a high quality financial report with less information asymmetry and less bad news hoarding, which contributes to less EM activities, lower bank crash and distress risks (Jin, Kanagaretnam, Lobo and Mathieu, 2013; Biddle, Ma and Song, 2016; Li, Ma and Song, 2018).

3.3 Empirical literature review

3.3.1 Signalling role of earnings management (EM)

The informational role of EM activities on future bank performance using DLLPs has been documented by previous studies. Wahlen (1994) investigates U.S. commercial banks from 1987 to 1995. He finds that commercial banks' DLLPs are positively associated with changes in subsequent cash flows and returns only when unexpected changes in non-performing loans and unexpected charge-offs are controlled. The author also documents that banks' stock returns react positively to the announcement of a high level of unexpected LLPs. Later on, Beaver and Engel (1996) study U.S. sample banks from 1977 to 1991 and document an inconsistent association between DLLAs and banks' future stock prices. Additionally, they find no association between DLLPs and banks' future net income.

Contrary to prior studies, Ahmed, Takeda and Thomas (1998) document a negative signalling role of DLLPs on future earnings changes and stock returns, based on a sample of banks over the period 1986 to 1995. The finding is inconsistent with prior studies. They suggest that the inconsistency is driven by different measurements of DLLPs and estimated periods. Recently, Morris, Kang and Jie (2016) find evidence suggesting that DLLPs are used for smoothing current earnings and signalling future earnings. Using a sample of banks across the period 2006-2010, they find that banks with a higher level of DLLPs are more likely to have above-average earnings changes that are pre-managed than other banks in the next accounting period, which means that they are riskier in the near future.

Different from above mentioned studies, Cohen, Cornett, Marcus and Tehranian (2014) use both DLLPs and discretionary security gains and losses to measure EM and signal future performance in the banking industry. They investigate whether EM causes extreme returns of public banks, before (1997-2006) and during the financial crisis period (2007-2009). They hypothesize that both positive and negative EM to lead to similar economic effects, suggesting that a reversal normally appears after artificially manipulating earnings. Using an ex-ante three-year absolute value of EM to capture banks' EM behaviour, they find a positive association between pre-crisis EM (the absolute value) and tail risks during the financial crisis period, whereas no significant association is documented during the pre-crisis period. They also find that aggressive earnings manipulators significantly underperform conservative manipulators during the financial crisis period.

3.3.2 Signalling role of bank efficiency (BE)

Prior studies have documented the signalling role of operational efficiency and technical efficiency on firm performance in the U.S. non-financial industries. (Alam and Sickles, 1998; Greene and Segal, 2004; Baik, Chae, Choi and Farber, 2013, etc.). As for the U.S. financial industry, especially the banking industry, only a few empirical studies have estimated the informational role of BE. Humphrey and Pulley (1997) document that BE positively signals the increase of profits in the U.S. banking industry. Meles, Porzio, Sampagnaro and Verdoliva (2016) investigate a unique type of efficiency of U.S. commercial banks, which is intellectual capital efficiency. They find that the intellectual capital efficiency positively signals banks' profitability, measured by return on average assets and return on average equity.

The informational role of BE on risk taking in the U.S. banking industry has also been studied. Ding and Sickles (2018) estimate the impact of cost efficiency on U.S. banks' capital structure and portfolio risk levels. Their results suggest that efficient banks hold more capitals than inefficient ones. They also document that efficient banks tend to take more credit risks while reduce their risk-weighted assets simultaneously. As BE affects banks' preference of taking risks, it may further impact banks' decisions of exiting the market. Wheelock and Wilson (2000) study the determinants of U.S. banks' market exits via acquisition and bankruptcy from the mid-1930s to 1970s. They find that banks with higher cost efficiency have a higher probability of failure and lower risks of being acquired than inefficient ones.

Spokeviciute, Keasey and Vallascas (2019) also investigate the exit determinants of U.S. commercial banks using a sample from 1984 to 2013. Spokeviciute, Keasey and Vallascas (2019) study the determinants of the exits during the subperiods including the non-crisis period, the savings and loans crisis period and the global financial crisis period. They document that pre-crisis inefficient banks have a higher market exit rate both via failure and acquisition than efficient banks. They further find that this phenomenon is even more significant during the financial crisis periods when there is no government intervention, such as TARP fund injections. Their study highlights the signalling role of BE on bankruptcy and acquisition.

This study estimates the signalling role of BE on banks' future profitability and asset quality, and further interacts BE with EM to stabilize the signalling impacts.

3.3.3 Signalling role of managerial ability (MA)

A few studies have documented the signalling role of MA in non-financial industries. Chemmanur and Paeglis (2005) find that firms with capable managers outperform other new issuers following IPOs. Leverty and Grace (2012) suggest that MA can inversely signal firms' likelihood of failure and the costs of failure. Demerjian, Lev, Lewis and McVay (2013) document that able managers are more responsible towards firms' financial statements. Therefore, they are less likely to manipulate earnings. They also find a positive association between MA and earnings over a three-year period.

The signalling role of MA in the banking industry has also been investigated. Barr, Seiford and Siems (1993) document that management quality, measured by managerial efficiency using a DEA model, is able to signal the failure of U.S. banks. Beatty and Liao (2011) find that well-managed banks can better forecast and recognize loan losses, thus they are more likely to have adequate capital during recessions than poorly managed banks. Their findings suggest the signalling role of managerial quality on bank capital adequacy.

Recently, Andreou, Philip and Robejsek (2016) study the effect of bank managers' MA on liquidity creation and risk preferences among U.S. banks, where the liquidity creation is one of the major services that banks provide to stimulate the economy. They use Stochastic Frontier analysis (SFA) model to estimate bank efficiency and model the bank efficiency using OLS regressions. The MA is the residual subtracted from the bank efficiency model. Their results indicate that past year's MA is significantly and positively associated with current year's bank performance, measured by return on assets and return on equity. They also find that bank managers' risk-taking behaviour is positively associated with their abilities. Moreover, MA is found to positively affect future bank liquidity creation, especially for small and medium banks. Their findings shed light on the informational role of MA on banks' future liquidity and profitability.

García-Meca and García-Sánchez (2018) study the association between MA and earnings quality in the banking industry. They use a Data Envelopment analysis (DEA) model to obtain bank efficiency scores and use the discretionary bank efficiency to evaluate MA. Earnings quality is evaluated by banks' earnings persistence and future cash flows. Their evidence shows that banks' MA is positively associated with earning persistency, which means that banks with capable managers consistently generate more profits in the future. Their finding also refers to the informational role of MA on future bank profitability.

Banna, Ahmad and Koh (2018) study the impact of MA on loan quality, using a sample of 581 U.S. commercial banks over the period 1991 to 2013. Consistent with the prior mentioned studies, their measure of MA is also derived from the model of bank efficiency. Their results suggest a positive association between MA and banks' loan quality. They further document that capable managers improve the quality of loan portfolios by effectively monitoring the behaviour of borrowers. Their finding implies that MA is able to signal the quality of bank loans.

Our study investigates the signalling role of MA on banks' future profitability and asset quality, and further interact MA with EM to stabilize the signalling impacts.

3.4 Hypotheses

3.4.1 Impacts from EM, BE and MA

Income-increasing EM activities are manipulation scandals, they are negative information that banks prefer to hide from the public, causing information asymmetry. Thus, EM is positively associated with information asymmetry (De Franco, Hope and Lu, 2017). The manipulation scandals that banks hide from the public could be uncovered due to the lack of loan loss provisions at a future point, which affects the reputation of those banks, and consequently affect their future profitability and asset quality in a negative way. On the other hand, banks that conduct income-decreasing EM tend to smooth additional earnings that are above their target earnings. They conduct earnings manipulation by increasing their LLPs, which contributes to LLRs. Sufficient LLRs (accumulated LLPs) decrease the default risks of banks. Therefore, even though these banks are also called earnings manipulators, their future performance are unlikely to suffer from their EM activities. In contrast, these banks are expected to perform better than others, because they have relatively high reputation due to their low default risks. Additionally, when the amount of LLRs, that banks hold, are more than the amount that they are required in an accounting year, they can potentially prepare relatively less LLPs in the next accounting year, as long as the amount of LLRs meets the requirements suggested by SFAS. Less loan loss provisions means that banks can potentially report more net operating profits. Therefore, EM is expected to have a negative association with subsequent bank performance.

BE is able to affect banks' capital and risk-taking preferences. Per Ding and Sickles (2018), efficient banks retain more capitals, take more credit risks, and have less risk-weighted assets than inefficient banks. Risks are likely to be positively associated with profitability when banks are efficient, thus efficient banks are expected to generate more profits in the near future. Also, low risk-weighted assets and high levels of capital holdings suggest an optimum capital structure, thence we also expect corresponding banks to keep their high-quality assets in the near future. Efficient banks are more likely to survive and prosper than inefficient banks due to their advantages in innovation, thus efficient banks are more competitive than inefficient ones. Competitive banks are better at allocating capital funds to achieve better financial access, operation development, and financial stability than their counterparts (Chronopoulos, Liu, McMillan and Wilson, 2015). Therefore, we expect efficient banks to achieve better performance subsequently.

BE positively signals future bank performance, whilst EM negatively signals the bank performance. Efficient banks can choose to perform income-increasing EM due to their business strategies or by chance, making EM and BE to have opposite signals towards future bank performance. Under this case, using BE and EM separately can hardly signal future bank performance. To address this concern, we suggest to interact EM and BE indicators to generate a new variable called accounting managerial behaviour (AMB). Following the interaction, efficient banks that conduct income-decreasing EM (large BE and small EM) are supposed to outperform other banks, and inefficient banks that involve in income-increasing EM (small BE and large EM) are expected to underperform their counterparts in the near future.

The difficulties in judging whether EM or BE has more of a impact on future bank performance leads to the difficulties in comparing the bank performance of efficient banks that conduct income-increasing EM and inefficient banks that engage in income-decreasing EM. Consequently, this chapter mainly focuses on studying the performance of inefficient banks that conduct income-increasing EM and efficient banks that conduct income-decreasing EM.

Accordingly, we test the following hypothesis.

H1a. Inefficient banks that engage in income-increasing EM underperform their peers in the next fiscal year.

H1b. Efficient banks that engage in income-decreasing EM outperform their peers in the next fiscal year.

"Managerial abilities are important in the banking industry due to the large information asymmetries, opaqueness, and complexities of this sector." -- García-Meca and García-Sánchez (2018)

Managers can influence the voluntary corporate financial disclosure (Chemmanur and Paeglis, 2005). Able managers help eliminate information asymmetry by effectively conveying and presenting intrinsic values of firms more credibly (Chemmanur and Paeglis, 2005; De Franco, Hope and Lu, 2017). Therefore, able managers are more likely to disclose accurate forecasts (Baik, Farber and Lee, 2011), which implies that their banks may have less unfavourable information to hide from the public. Therefore, we expect banks that employ able managers to perform better than their counterparts subsequently. Additionally, able managers work more efficiently than relatively incapable managers. They are more likely to select and implement better projects, and to make better decisions that contribute to better operating performance in the near future (De Franco, Hope and Lu, 2017; Chemmanur and Paeglis, 2005). Managers with high ability can also evaluate and monitor loan borrowers better than other managers, to achieve more revenues (Banna, Ahmad and Koh, 2018). Moreover, high-ability managers are likely to draw better business plans that aim to achieve consistent benefits, instead of focusing only on short-term profits. Therefore, banks that are managed by ably managers are expected to have a better future performance than other banks.

MA positively signal future bank performance, whilst EM negatively signal future bank performance. Similar as our previous statement that efficient banks can potentially choose to conduct income-increasing EM, banks with able managers can also choose to conduct income-increasing EM because of their business strategies or by chance. Under this case, using MA and EM individually can hardly signal future bank performance, because those two indicators provide opposite signals. To address this concern, we suggest to interact MA and BE indicators, and also name the interaction as AMB. After the interaction, banks with able managers who conduct income-decreasing EM (large MA and small EM) are expected to outperform their peers, and banks with unable managers who conduct income-increasing EM (small MA and large EM) are supposed to underperform other banks in the following year.

It is hard to determine whether the impact of EM on future bank performance overtakes the impact of BE on the performance. This means that the performance of banks with able managers who conduct income-increasing EM (large MA and small EM), and that of banks with unable managers who conduct income-increasing EM (small MA and large EM), can hardly be compared. Therefore, these two types of banks are not compared with each other in our analysis.

Accordingly, we test the following hypotheses.

H1c. Banks with an unable manager who manipulates earnings underperform their peers in the coming year.

H1d. Banks with an able manager who manipulates earnings downwards outperform their peers in the coming year.

In general, the hypotheses in this section can be summarized as follows.

Proposition 1: Banks with superior AMB outperform their peers, whilst banks with poor AMB underperform their peers in the next fiscal year.

3.4.2 Size effect and AMB

Demsetz and Strahan (1997) and Stever (2007) argue that larger banks are more likely to be diversified, however, their further findings towards banks' risk takings differ. Demsetz and Strahan (1997) propose that larger banks prefer lower capital ratios, therefore are riskier than smaller banks, but Stever (2007) finds that smaller banks are riskier. Their findings imply that small banks are risky due to their monotonous business, whereas large banks are risky because they pursue riskier strategies to achieve higher profits. The diversity of large banks refers to their ability of choosing borrowers with higher credit compared with smaller banks. Having more choices when picking up borrowers together with high efficiency and sufficient loan loss provisions (i.e. superior AMB), make those large banks to perform better than their peer banks in the near future, regardless of their risk-taking levels. In contrast, it might be hard for banks that are inefficient or have unable managers with insufficient loan loss provisions to successfully handle diversified business due to banks' overall inability. Therefore, diversified business strategies could be riskier to banks with poor AMB than dull business strategies. Accordingly, we propose the following hypotheses.

H2a. For banks with superior AMB, their size positively affects their future performance.

H2b. For banks with poor AMB, their size negatively affects their future performance.

In general, the hypotheses in this section can be summarized as follows.

Proposition 2: The size effect on future bank performance can be dominated by banks' accounting managerial behaviour.

3.4.3 Additional hypotheses

- **Deposits** - Banks' level of deposits reflects their reputation and their ability to attract business. A high level of deposits is usually associated with a high-level profitability and asset quality due to the advantages in resources. Therefore, we expect a positive association between deposits and bank performance. Fries, Neven, Seabright and Taci (2006) use deposits as a control variable to model bank performance and find a positive association between deposits and bank performance.
- **Federal fund rate growth** - federal fund rate is the interest rate that banks use to lend to one another and trade with the Federal Reserve Bank. It is an effective indicator to evaluate the monetary policy due to its sensitivity in shocks of reserve supplies (Bernanke and Blinder, 1992). When federal fund rate hikes, profits for the banking sector increase. Therefore, we expect a positive association between federal fund rate growth the bank performance.
- **Competition** - Banks that have high competition in the industry are expected to produce more profitability as well as having better asset quality, because highly competitive banks usually have higher reputation and better resources than banks that have low competition in the banking industry. Therefore, we expect bank competition to positively affect bank performance.
- **Non-performing loans ratio** - Non-performing loans are the loans with a high level of default risks. Banks that have high level of default risks are expected have lower performance than other banks (Ahmed, Takeda and Thomas, 1998). Therefore, we expect a negative association between non-performing loans ratio and bank performance.
- **Net charge-offs ratio** - Non-performing loans could be charged off into gross charge-offs if the amount of debts can no longer be collected. Net charge-offs are the differences between gross charge-offs and recoveries of delinquent debt. Therefore, similar to non-performing loans ratio, we expect a negative association between net charge-offs ratio and banks' profitability.
- **Liquidity** - liquidity is banks' ability of converting assets into cash. Banks with a high level of liquidity have relatively higher reputation than other banks because they have less problems in withdraws. Banks with high reputation are likely to attract more

depositors, and are likely to perform well to keep customers than other competitors. Therefore, we expect a positive association between liquidity ratio and bank performance, which is consistent with the association documented by Chronopoulos, Liu , McMillan and Wilson (2015).

- **Return on assets ratio** - High asset quality contributes to low default risks, thus banks with a high level of asset quality are likely to produce more returns than other banks, which suggests a positive association between profitability and asset quality. Consequently, we expect a positive association between banks' return on assets and asset quality, which is consistent with the association documented by Ghosh (2015).

3.5 Data and variables

3.5.1 Data

The main database used in this chapter is the Fitchconnect database, which mergers data from the former Bankscope database. Therefore, we expect the Fitchconnect database has reliable financial data for the worldwide banking industry. We firstly collect financial data of 982 U.S. commercial banks from the Fitchconnect database and retrieve macroeconomic data from the Federal Reserve Bank database, across the period 1998 to 2017. Then we remove non-consolidated bank observations, to avoid duplicated financial statements. We further remove observations with missing total assets value, since the total assets variable is one of the most essential variables in our estimations. Additionally, observations that have missing total assets data usually miss-report all other financial data in the Fitchconnect database. Our final sample consists of 589 U.S. commercial banks across the period 1998 to 2017, and the dataset for further estimations is unbalanced.

3.5.2 Main Variables

This section consists of three parts. The first part introduces measures of EM, the second part captures the measure of BE and the third part presents the measure of MA.

Earnings management (EM)

We define loan loss provisions (LLPs) based EM as earnings management indicator 1 (EM1) and define loan loss reverses (LLRs) based EM as earnings management indicator 2 (EM2). In this chapter, an increase in EM suggests that banks boost earnings by artificially decreasing LLPs and LLRs. LLRs are accumulated LLPs over several years, which means EM2 eliminates the volatility of LLPs over several periods, while EM1 only focuses on LLPs in a given year. Most studies only use LLPs to capture EM, however, EM directions could vary based on various factors in a fiscal year, making EM1 relatively unstable. Therefore, it is beneficial to also investigate the impact of EM on bank performance using both LLPs-based EM and LLRs-based EM.

Following Adams, Carow and Perry (2009), EM is evaluated based on discretionary loan loss provisions (DLLPs) and discretionary loan loss reserves (DLLRs). We firstly estimate loan loss provisions ratio (LLPs) and loan loss reserves ratio (LLRs) using the following equations, respectively.

$$LLP_{it} = \alpha + \beta_1 Ln(assets)_{it} + \beta_2 \Delta NPA_{it} + \beta_3 \frac{Chargeoffs_{it}}{Aloans_{it}} + \beta_4 \frac{LLP_{i,t-1}}{Aloans_{it}} + year\ dummies + \varepsilon_{it} \tag{17}$$

$$LLR_{it} = \alpha + \beta_1 Ln(assets)_{it} + \beta_2 \Delta NPA_{it} + \beta_3 \frac{Chargeoffs_{it}}{Aloans_{it}} + \beta_4 \frac{LLR_{i,t-1}}{Aloans_{it}} + year\ dummies + \varepsilon_{it} \tag{18}$$

Where equation (17) and equation (18) model the loan loss provisions ratio and loan loss reserves ratio, respectively. Definitions of explanatory variables are displayed in Appendix B. We obtain DLLPs (DLLRs) by subtracting the nondiscretionary component of LLPs (LLRs) from the expected level of LLPs (LLRs). This means that the residual (ε_{it}) from equation (17) and equation (18) captures the level of DLLPs and DLLRs, respectively. We then take the negative values of DLLPs and DLLRs as our final measures of EM, naming EM1(-DLLPs) and EM2(-DLLRs), respectively, to better fit earnings management's economic meaning. A large positive value of EM1 (or EM2) indicates a high level of income-increasing EM and a small negative value of EM1 (or EM2) notifies a high level of income-decreasing EM. We use DLLPs as our main measure of EM instead of discretionary choices in the realised security gains and losses, because DLLPs are found to be far more efficient in capturing banks' EM behaviour than the realised security gains and losses (Cohen, Cornett, Marcus and Tehranian, 2014).

Bank efficiency (BE)

Per previous studies, BE can be measured using parametric and non-parametric approaches. Data Envelopment Analysis (DEA) is the most well-known non-parametric analysis and Stochastic Frontier Analysis (SFA) is one of the primary parametric methods. SFA depends on a specific function to define an efficient frontier, however, the selected frontier function could induce inductive bias in the stochastic process and further cause degradation problems in obtained efficiency scores when the data tendency is inconsistent. The DEA approach, on the other hand, does not depend on a frontier function nor a probability distribution; therefore, it avoids misspecification errors and provides more flexibility towards various data shapes (Silva, Tabak, Cajueiro and Dias, 2017). In this study, we have no interest in a BE prediction, making designing efficient frontier and probability distribution unnecessary. Consequently, we choose DEA as our main method to evaluate banks' technical efficiency.

We apply a multi-stage input-oriented DEA method proposed by Coelli (1998). Three inputs and three outputs are chosen to evaluate technical efficiency of US banks. Following Harris, Huerta and Ngo (2013), we select non-interest expenses to assets ratio (NIETA), interest expenses to assets ratio (IETA) and deposits to assets ratio (DTA) as input variables, and adopt loans to assets ratio (LTA), non-interest incomes to assets ratio (NIITA) and interest incomes to assets ratio (IITA) as output variables. We conduct the DEA model for each estimated year, respectively, to eliminate year effects in the model.

The DEA model is designed as follows. First, we model a radial linear programming (LP) equation set as follows.

$$\begin{aligned} & min_{\theta,\varphi} \ \theta \\ & s.t. \quad -y_i + Y\varphi \geq 0 \\ & \qquad\quad \theta x_i - X\varphi \geq 0 \\ & \qquad\quad \varphi \geq 0 \end{aligned} \tag{19}$$

Where θ is a scalar and φ is a constant of $M\times 1$vector; M denotes the number of estimated banks; x_i and y_i are input and output vector of the bank i, respectively; X and Y are both $3\times M$ matrices.

Second, maximizing the sum of slacks in a second stage LP.

$$\begin{aligned} & min_{\varphi,OS,IS} \ \theta \\ & s.t. \quad -y_i + Y\varphi - OS \geq 0 \\ & \qquad\quad ax_i - X\varphi - IS \geq 0 \\ & \qquad\quad \varphi \geq 0, OS \geq 0, IS \geq 0 \end{aligned} \tag{20}$$

Where IS is a 3×1 vector of input slacks; OS is a 3×1 vector of output slacks; ax_i denotes θx_i, where the value of θ is obtained in equation (19), it is an input vector for bank i. This equation identifies banks that have efficiency slacks, named slack-remained banks.

Third, focus on detecting all input dimensions that retain slacks out of slack-remained banks. All inputs are tested individually using the following LP model; the achievement of contracting indicates the existent of a slack in the corresponding input.

$$\begin{aligned} & min_{\theta,\varphi} \ \theta \\ & s.t. \quad -y_i + Y_e\varphi \geq 0 \\ & \qquad\quad \theta a x_i^j - X_e^j\varphi \geq 0 \\ & \qquad\quad a x_i^{\neq j} - X_e^{\neq j}\varphi \geq 0 \\ & \qquad\quad \varphi \geq 0 \end{aligned} \tag{21}$$

Where Y_e refers to a $3 \times M_e$ an output matrix of all efficient banks, M_e is the number of efficient banks in the estimated dataset; superscript "j" identifies an indicator of input; superscript "$\neq j$" refers to all other inputs except j; X_e^j denotes a vector for jth inputs among all efficient banks; $X_e^{\neq j}$ represents a vector for all inputs except the input j, among all efficient banks; a is the value of θ obtained from equation (19); x_i^j denotes a vector of input j of bank i; and $x_i^{\neq j}$ denotes a vector of all inputs excluding the jth input for bank i.

Fourth, conduct the following LP to achieve a radial reduction in all inputs that have slacks.

$$min_{\theta,\varphi}\ \theta \tag{22}$$

$$\begin{aligned} s.t. \quad & -y_i + Y_e\varphi \geq 0 \\ & \theta a x_i^s - X_e^s\varphi \geq 0 \\ & a x_i^{ns} - X_e^{ns}\varphi \geq 0 \\ & \varphi \geq 0 \end{aligned}$$

Where superscript "s" represents all slack-remained inputs of bank i and X_e^s denotes corresponding slack-remained inputs of all efficient banks; superscript "ns" identifies remaining inputs without slacks of bank i and X_e^{ns} refers to corresponding remaining inputs among all efficient banks.

Fifth, if there are still slacks existing in some dimensions of the inputs, take the projected points identified from equation (22), based on the value of θ, and loop equations (21) and (22), until no slacks left in input variables.

Finally, retain the projected points trained from equation (22), and loop equations (19)-(21) to conduct radial reduction trainings for the output variable until eliminating all output slacks. Then φ vector obtained in the end can assist identifying projected points for inefficient banks on the efficient frontier, and the efficiency score can be derived by dividing the projected value of vectors from the original value of vectors. The higher efficiency scores, the better bank performance.

Managerial ability (MA)

We evaluate MA of commercial banks by disentangling it from bank-specific factors in the BE model. BE, as a dependent variable, is obtained from the DEA approach stated above. We model BE using equation (23) following Demerjian, Lev and McVay (2012) and Andreou, Philip and Robejsek (2016), and use residual (ε) to measure the raw MA value

(RMA). The year effect is controlled in the model, and the explanatory variables' definitions are displayed in Appendix B.

$$BE_{it} = \alpha + \beta_1 Ln(assets)_{it} + \beta_2 Ln(employee)_{it} + \beta_3 Ln(age)_{it} + \beta_4 Leverage_{it} + \beta_5 FCF_{it} + \varepsilon_{it} \quad (23)$$

The above equation derives both positive and negative RMA, where the negative value represents the corresponding bank's manager has a negative ability towards supervising a bank. Economically, it is unreasonable to state that a manager has a negative ability. Therefore, we proposed a transformation approach to formalize RMA. The formalization also contributes to bonding the new managerial ability value (MA) between 0 and 1, which makes the level of MA easier to be classified and identified. MA equals 0.5 indicates that the manager's abilities have no effect on bank efficiency. MA belows 0.5 denotes the manager has comparatively low abilities, which are negatively affecting the BE. The smaller the MA, the worse it affects the BE. MA above 0.5 signifies that the manager's abilities have positive impacts on the BE. The larger the MA, the better it affects the BE. We formalize the transformation on year basis, specified as follows.

$$MA_{i,t} = \frac{1}{1 + e^{\left(-\frac{5.8}{max_t - min_t} * RMA_{i,t}\right)}} \quad (24)$$

Where i is the indicator of bank; t denotes the year; max_t represents the maximum value of RMA at year t; and min_t denotes the minimum value of RMA at year t. We use formula $\frac{5.8}{max_t - min_t}$ to disperse the original RMA distribution, since the maximum value of RMA is 0.7085 and the minimum value is -0.5231, the dataset clusters too much to be transformed by an exponential formula.

We set p equals to 2.9 to make equation $M1 = \frac{1}{1+e^{-p}} = 0.95$ and $M2 = \frac{1}{1+e^{p}} = 0.05$. We do not endow p a larger value in order to avoid $M1$ and $M2$ being too close to 1 and 0, respectively; otherwise, the distribution of RMA might be changed dramatically. For instance, if we set p as 10, a considerable amount of RMA will be transformed to a value extremely close to 0 or 1, which could ruin the original RMA distribution. The value 5.8 comes from p times 2, we multiply p by 2 times because our mean value is approximate to 0. One can also subtract mean value from RMA using equation (25), if the mean value is significantly different from zero.

$$MA_{i,t} = \frac{1}{1 + e^{\left(-\frac{5.8}{max_t - min_t} * (RMA_{i,t} - mean_t)\right)}} \tag{25}$$

Equation (25) can help transform any data series with a negative minimum value and a positive maximum value, to a series with a range between 0 and 1, without losing the mean value (e.g. in our sample, equals to 0.5 after the transformation) in the original dataset. This transformation can also help to define and level variables in a clear range, as well as reforming over-dispersed/over-aggregated dataset. For dataset that both minimum and maximum values are positive, we suggest using equation (25) for transformation, while for dataset that both minimum and maximum values are negative, we suggest using (RMA + mean value of RMA) to substitute RMA in equation (24) and then perform the transformation.

3.6 Empirical analysis design

The main purpose of this research is to study the impact of AMB on banks' future performance. We use profitability and asset quality to evaluate banks' future performance, where the profitability is measured by the ratio of net income to total assets (PM1) and post-tax profit to total equity ratio (PM2). The asset quality is measured by a ratio of reserves for impaired loans to gross loans (AQ1) and a ratio of loan loss provisions to total loans (AQ2).

We first investigate the signalling role of EM, BE and MA by ranking them into three groups by year, respectively. The group specification of three main variables are displayed in Graph 1, where Group a1, Group a2 and Group a3 represent the small, medium and large value groups, respectively. We then conduct difference in mean tests between banks in Group a1 and Group a3 on their future profitability and asset quality. Banks that conduct income-increasing EM (Group a3) are expected to achieve lower asset quality and produce lower profitability than banks that conduct income-decreasing EM (Group a1) in the next fiscal year. Additionally, banks having high-ability managers (Group a3 of MA) and high efficiency (Group a3 of BE) are expected to generate more benefits, and have higher asset quality than banks from Group a1, respectively.

EM, BE and MA individually can hardly successfully signal banks' future performance due to the mixed signalling noises caused by individual indicators. Therefore, we then interact EM with BE and MA to study the impact of AMB on future bank performance. To do this, we introduce four group-interacted variables, EM1*BE, EM2*BE, EM1*MA and EM2*MA. Graph 2 presents compositions of groups, where Group 1 represents banks that belong to Group a3 of EM and Group a1 of BE (or MA). Group 9 denotes a combination of EM Group a1 and BE (or MA) Group a3. We expect banks in Group 1 to have poorer future performance than banks in Group 9. Banks from Group 9 are recognized as banks with superior AMB, and banks belonging to Group 1 are banks with poor AMB.

In this study, BE represents the productive ability of banks, which contains the ability of managers. Additionally, from a statistical point of view, MA is derived from a model of BE, they are highly likely to be correlated to some extent. Therefore, we do not interact EM with both BE and MA to drive AMB.

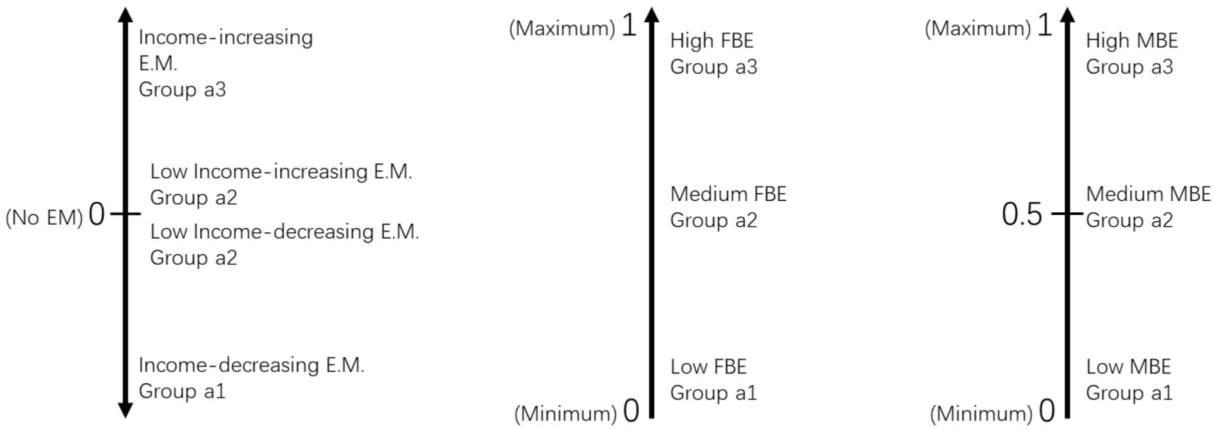


Figure 1 Group construction of earnings management (EM), bank efficiency (BE) and managerial ability (MA).

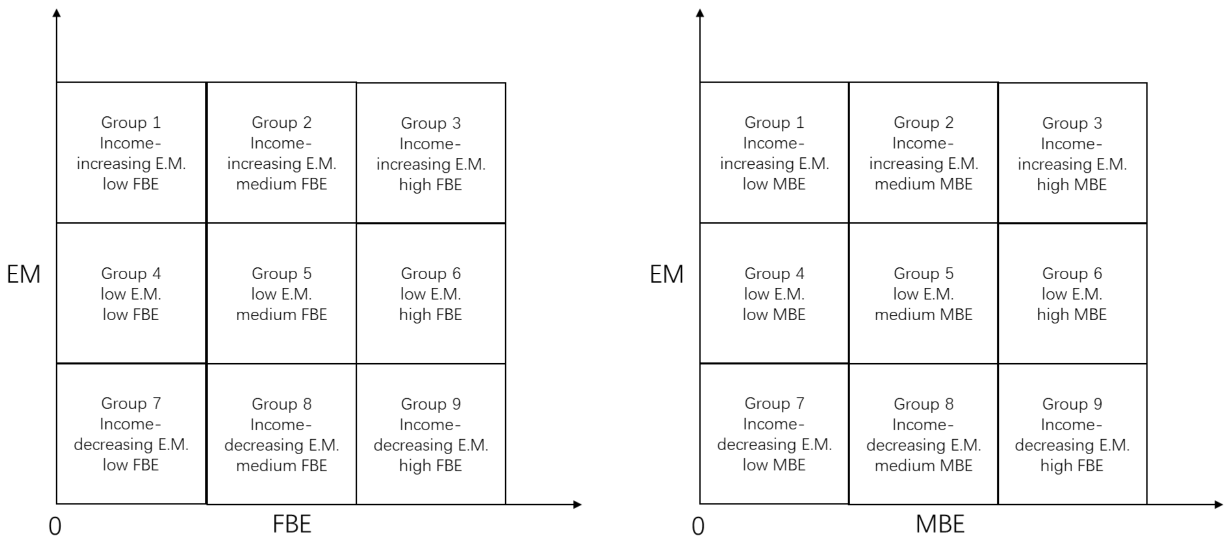


Figure 2 Group construction of accounting managerial behaviour (AMB).

Univariate tests could present a rough association between AMB and U.S. banks' future profitability (PM) and asset quality (AQ), however, the results retain noises from other bank attributes. For instance, previous studies find that small banks are more profitable than large ones (Hoffmann, 2011; Andreou, Philip and Robejsek, 2016). This means that even we find an association between AMB and banks' future performance, it could be potentially driven by missing factors such as bank size. To address this concern, we further apply multivariate tests to control for the impacts of additional bank characteristics. We use Ordinary Least Squares (OLS) regression as our baseline model, controlling for firm-fixed effect and year-fixed effect. We also adopt robust standard errors to eliminate the impacts from heteroscedasticity. An unbalanced dynamic panel dataset is applied, and the regressions take the following forms.

$$\begin{aligned} PM_{i,t+1} = \alpha &+ \beta_1 EM\_dum_{it} + \beta_2 ID\_dum_{it} + \beta_3 Ln(deposits)_{i,t+1} + \beta_4 FRG_{t+1} \\ &+ \beta_5 HHI_{i,t+1} + \beta_6 NPLER_{i,t+1} + \beta_7 LAWF_{i,t+1} \\ &+ \beta_8 Charge - offs_{i,t+1} + \beta_9 PM_{it} + \varepsilon_{it} \end{aligned} \tag{26}$$

$$\begin{aligned} AQ_{i,t+1} = \alpha &+ \beta_1 EM\_dum_{it} + \beta_2 ID\_dum_{it} + \beta_3 Ln(deposits)_{i,t+1} + \beta_4 FRG_{t+1} \\ &+ \beta_5 HHI_{i,t+1} + \beta_6 NPLER_{i,t+1} + \beta_7 LAWF_{i,t+1} + \beta_8 ROA_{i,t+1} \\ &+ \beta_9 LATA_{i,t+1} + \beta_{10} AQ_{it} + \varepsilon_{it} \end{aligned} \tag{27}$$

Where $PM_{i,t+1}$ denotes profitability of bank i at year $t+1$, and we use two ratios ($PM1$ and $PM2$) to capture the profitability. $PM1$ is a ratio of net income to total assets and $PM2$ is post-tax profit to total equity ratio. PM_{it} captures the profitability of bank i at year t, which controls for the dynamic effects from the dependent variable PM. $AQ_{i,t+1}$ represents asset quality for bank i at year $t+1$, we use $AQ1$ (reserves for impaired loans to gross loans ratio) and $AQ2$ (loan loss provisions to total loans ratio) to evaluate AQ; AQ_{it}denotes the asset quality of bank i at year t, capturing for the dynamic impacts from the dependent variable AQ. EM refers to either $EM1$ or $EM2$, and EM_dum equals to one for banks in Group a3 of EM, and equals to zero for banks in Group a1 of EM. ID represents either BE or MA, and ID_dum equals one for banks in Group a3 of ID, and equals zero for banks in Group a1 of ID. Definitions of control variables are presented in Appendix B.

Next, we conduct OLS regressions using interactions as our main variable of interests, to possibly increase the signalling power of AMB on future bank performance. The models are specified as follows.

$$\begin{aligned} PM_{i,t+1} = \alpha &+ \beta_1 AMB\_group9_{it} + \beta_2 AMB\_group1_{it} + \beta_3 Ln(deposits)_{i,t+1} \\ &+ \beta_4 FRG_{t+1} + \beta_5 HHI_{i,t+1} + \beta_6 NPLER_{i,t+1} + \beta_7 LAWF_{i,t+1} \\ &+ \beta_8 Charge - offs_{i,t+1} + \beta_9 PM_{it} + \varepsilon_{it} \end{aligned} \tag{28}$$

$$AQ_{i,t+1} = \alpha + \beta_1 AMB\_group9_{it} + \beta_2 AMB\_group1_{it} + \beta_3 Ln(deposits)_{i,t+1} + \beta_4 FRG_{t+1} + \beta_5 HHI_{i,t+1} + \beta_6 NPLER_{i,t+1} + \beta_7 LAWF_{i,t+1} + \beta_8 ROA_{i,t+1} + \beta_9 LATA_{i,t+1} + \beta_{10} AQ_{it} + \varepsilon_{it} \tag{29}$$

Where AMB_group9 (AMB_group1) equals one for banks from Group 9 (Group 1) of AMB, zero otherwise. AMB is the interaction of EM and BE (or MA). Specifically, AMB_group9 (AMB_group1) represent $EM1BE\_group9$ ($EM1BE\_group1$), $EM2BE\_group9$ ($EM2BE\_group1$), $EM1MA\_group9$ ($EM1MA\_group1$), and $EM2MA\_group9$ ($EM2MA\_group1$). For instance, $EM1BE\_group9$ is a dummy variable valued one for banks in Group 9 of the EM1*BE based AMB, valued zero for banks in other groups of the EM1*BE based AMB.

3.7 Empirical results and discussion

This section reports analysis results from univariate tests, baseline approaches, robustness checks and models considering the size effects.

3.7.1 Future performance differences

Table 14 summarizes our main variables, EM, BE and MA, by year. The mean value of both EM measures (EM1 and EM2) equal to zero, and the mean value of BE and MA varies with year. The computation of BE and MA indicators makes them free from year impacts. Therefore, the fluctuated mean value suggests that banks' MA and BE change constantly even after removing the annually macroeconomic effect during the estimated period. The number of observations we estimated for each year are analogous, apart from the initial two years (1998 and 1999), where the available sample data is limited. Additionally, we observe a relatively high EM1 volatility at year 2000 and a relatively low BE at year 2001.

Table 15 presents the results of difference in mean tests between Group a1 and Group a3 of EM1, EM2, BE and MA on future performance of commercial banks, respectively. The results show that banks in Group a3 of EM1 and EM2 have significantly lower post-one-year AQ1 than the corresponding banks in Group a1. This evidence implies that banks conducting income-increasing EM have lower accumulated asset quality than banks performing income-decreasing EM in one-year time. The results also indicate that banks within the lowest value group (Group a1) of BE and MA have significantly lower profitability (PM) in the next fiscal year than banks belonging to the highest value group (Group a3) of BE and MA, respectively. These results are consistent with findings from Humphrey and Pulley (1997) and Andreou, Philip and Robejsek (2016), who document that BE and MA positively predict banks' profitability, respectively.

However, not all results from this table fit our expectations. The difference between Group a3 and Group a1 of EM1 on PM1 is positively significant from Table 15, which opposes our expectation. This may be caused by potential noises from uncontrolled attributes on banks' profitability. The rest of the t-test results are insignificant in the table, suggesting that EM1, EM2, BE and MA, individually, can barely contribute to a favourable signal towards future bank performance. Hence, the interactions of EM, BE and MA are generated to increase the signalling power on future bank performance. The univariate tests results based on interactions are reported in Table 16.

In Table 16, we interact EM1 and EM2 groups with BE and MA groups, respectively, and the interactions are called AMB. We expect future performance of banks in Group 9 to be significantly higher than banks in Group 1-8, whereas Group 1 is expected to underperform Group 2-9. Our results show significantly negative differences in most t-tests, which fits our expectation that superior AMB banks outperform their peer banks, whilst poor AMB banks underperform their peer banks in the subsequent year. Our evidence further implies that AMB is able to signal future bank performance more than individual attributes. We also observe some insignificant t-test results especially on AQ2 in Table 16, which could due to uncontrolled factors like year effects.

Table 14 Descriptive statistics of sample banks by year

This table presents descriptive statistics of earnings management (EM), bank efficiency (BE) and managerial ability (MA) indicators by year. EM is measured by the negative value of discretionary loan loss provisions (EM1) and by the negative value of discretionary loan loss reserves (EM2).

	Earnings management 1 (EM1)			Earnings management 2 (EM2)			Bank efficiency (BE)			Managerial ability (MA)		
Year	Obs.	Mean	Std.	Obs.	Mean	Std.	Obs.	Mean	Std.	Obs.	Mean	Std.
1998	\	\	\	\	\	\	195	0.842	0.087	131	0.482	0.222
1999	170	0.000	0.400	171	0.000	0.457	196	0.822	0.096	136	0.467	0.214
2000	392	0.000	1.189	393	0.000	0.517	420	0.803	0.087	294	0.484	0.202
2001	400	0.000	0.539	400	0.000	0.637	424	0.323	0.128	300	0.479	0.142
2002	409	0.000	0.371	409	0.000	0.439	432	0.634	0.133	311	0.486	0.185
2003	412	0.000	0.338	412	0.000	0.511	438	0.506	0.142	319	0.470	0.183
2004	411	0.000	0.675	411	0.000	0.643	438	0.701	0.103	319	0.486	0.179
2005	413	0.000	0.540	413	0.000	0.403	436	0.486	0.129	324	0.490	0.159
2006	422	0.000	0.390	422	0.000	0.300	448	0.748	0.105	341	0.487	0.189
2007	423	0.000	0.302	423	0.000	0.704	440	0.635	0.106	342	0.486	0.142
2008	426	0.000	0.506	426	0.000	0.617	410	0.506	0.126	330	0.492	0.151
2009	419	0.000	0.732	421	0.000	0.733	414	0.529	0.124	337	0.477	0.163
2010	410	0.000	0.639	411	0.000	0.657	423	0.611	0.120	364	0.491	0.185
2011	433	0.000	0.574	435	0.000	0.602	422	0.495	0.121	368	0.487	0.151
2012	428	0.000	0.518	429	0.000	0.416	433	0.599	0.129	374	0.486	0.186
2013	433	0.000	0.441	435	0.000	0.445	433	0.613	0.125	376	0.490	0.194
2014	425	0.000	0.326	427	0.000	0.359	428	0.593	0.137	380	0.493	0.176
2015	416	0.000	0.236	418	0.000	0.355	420	0.595	0.124	384	0.495	0.204
2016	400	0.000	0.289	401	0.000	0.267	402	0.685	0.130	379	0.500	0.221
2017	396	0.000	0.280	396	0.000	0.293	397	0.681	0.125	374	0.495	0.177
Total	7,638	0.000	0.534	7,653	0.000	0.514	8,049	0.608	0.169	6,483	0.487	0.181

Table 15 Earnings management (EM), bank efficiency (BE), managerial ability (MA) and future bank performance differences

This table reports the univariate analysis results of mean future bank performance by EM, BE and MA tertiles, respectively. The future bank performance is measured by profitability (PM) and asset quality (AQ) of the year following the base year, respectively. The measure PM comprises PM1 and PM2, where PM1 is the ratio of net income to total assets, and PM2 is the ratio of post-tax profit to total equity. The measure AQ comprises AQ1 and AQ2, where AQ1 is the ratio of reserve for impaired loans to gross loans, and AQ2 is the ratio of loan loss provisions to total loans. Earnings management, bank efficiency and managerial ability indicators are ranked by tertiles in each year, respectively. EM is measured by the negative value of discretionary loan loss provisions (EM1) and by the negative value of discretionary loan loss reserves (EM2). Banks that are in group a1 of EM conduct income-decreasing (conservative) earnings management, and banks that are in group a3 of EM conduct income-increasing (aggressive) earnings management, based on the EM measured in the base year. Banks that are in group a1 of BE have the lowest efficiency and banks that are in group a3 of BE have the highest efficiency among others, based on the BE measured in the base year. Banks that are in group a1 of MA have unable managers, whilst banks that are in group a3 of MA have able managers compared with their peer banks, based on the MA measured in the base year. T-test of the differences in mean results are presented between group a1 and group a3.

			Profitability measures (PM)		Asset quality measures (AQ)	
	Mixed group		$PM1_{t+1}$	$PM2_{t+1}$	$AQ1_{t+1}$	$AQ2_{t+1}$
Earnings management1_t ($EM1_t$)	Group a1 (conservative)	value	0.768	8.110	1.887	0.890
		Obs.	2,371	2,371	2,371	2,370
	Group a2	value	0.961	9.929	1.370	0.475
		Obs.	2,375	2,374	2,375	2,374
	Group a3 (aggressive)	value	0.870	8.470	1.653	10.725
		Obs.	2,350	2,350	2,349	2,345
	Group a3 minus a1		0.102**	0.360	-0.234***	9.836
Earnings management2_t ($EM2_t$)	Group a1 (conservative)	value	0.828	8.135	2.075	10.813
		Obs.	2,378	2,378	2,377	2,374
	Group a2	value	0.919	9.852	1.405	0.547
		Obs.	2,371	2,370	2,371	2,367
	Group a3 (aggressive)	value	0.858	8.541	1.425	0.603
		Obs.	2,359	2,359	2,359	2,356
	Group a3 minus a1		0.031	0.407	-0.650***	-10.210
Bank efficiency$_t$ (BE_t)	Group a1(lowest/inefficient)	value	0.565	6.277	1.688	0.678
		Obs.	2,512	2,512	2,487	2,498
	Group a2	value	0.879	9.402	1.514	0.552
		Obs.	2,510	2,509	2,505	2,502
	Group a3 (highest/efficient)	value	1.261	12.054	1.663	10.354
		Obs.	2,471	2,471	2,460	2,456
	Group a1 minus a3		-0.696***	-5.778***	0.025	-9.676
Managerial ability$_t$ (MA_t)	Group a1 (lowest)	value	0.681	7.411	1.602	0.611
		Obs.	2,035	2,035	2,034	2,033
	Group a2	value	0.839	8.751	1.583	0.579
		Obs.	2,032	2,031	2,031	2,029
	Group a3 (highest)	value	1.212	11.085	1.681	12.422
		Obs.	2,018	2,018	2,018	2,013
	Group a1 minus a3		-0.531***	-3.674***	-0.079	-11.811

Note:
* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

Table 16 Accounting managerial behaviour (AMB) and future bank performance differences

This table reports the univariate analysis results of mean future bank performance by AMB groups, respectively. The future bank performance is respectively measured by profitability (PM) and asset quality (AQ) of the year following the base year. The measure PM comprises PM1 and PM2, where PM1 is the ratio of net income to total assets, and PM2 is the ratio of post-tax profit to total equity. The measure AQ comprises AQ1 and AQ2, where AQ1 is the ratio of reserve for impaired loans to gross loans, and AQ2 is the ratio of loan loss provisions to total loans. AMB indicators are interacted tertile groups of earnings management (EM) and bank efficiency (BE) (or managerial ability (MA)) and the group structure can be found in Graph 2. Note that EM is measured by the negative value of discretionary loan loss provisions (EM1) and by the negative value of discretionary loan loss reserves (EM2). This table compares the differences in means of future bank performance between AMB group 1 and the rest as well as AMB group 9 and the rest. T-tests results are reported accordingly.

			Profitability measures (PM)		Asset quality measures (AQ)	
	Mixed group		$\mathrm{PM1}_{t+1}$	$\mathrm{PM2}_{t+1}$	$\mathrm{AQ1}_{t+1}$	$\mathrm{AQ2}_{t+1}$
$\mathrm{EM1}_t * \mathrm{BE}_t$	Group 1-8	value	0.844	8.670	1.584	4.409
		Obs.	6,238	6,237	6,237	6,232
	Group 9	value	1.187	11.909	1.980	0.980
		Obs.	721	721	721	720
	(Group 1-8)-(Group 9)		-0.343***	-3.239***	-0.396***	3.429
	Group 2-9	value	0.915	9.368	1.617	4.488
		Obs.	6,186	6,185	6,186	6,181
	Group 1	value	0.589	0.431	1.688	0.578
		Obs.	773	773	772	771
	(Group 1) – (Group 2-9)		-0.326***	-3.259***	0.701	-3.910
$\mathrm{EM2}_t * \mathrm{BE}_t$	Group 1-8	value	0.838	8.715	1.562	0.604
		Obs.	6,254	6,253	6,253	6,247
	Group 9	value	1.263	11.600	2.171	34.236
		Obs.	716	716	716	713
	(Group 1-8)-(Group 9)		-0.425***	-2.885***	-0.610***	-33.633***
	Group 2-9	value	0.923	9.398	1.647	4.481
		Obs.	6,196	6,195	6,195	6,186
	Group 1	value	0.549	5.913	1.444	0.599
		Obs.	774	774	774	774
	(Group 1) – (Group 2-9)		-0.374***	-3.485***	-0.202***	-3.882
$\mathrm{EM1}_t * \mathrm{MA}_t$	Group 1-8	value	0.866	8.707	1.579	5.176
		Obs.	5,171	5,170	5,170	5,166
	Group 9	value	1.117	10.661	1.989	0.813
		Obs.	586	586	586	586
	(Group 1-8)-(Group 9)		-0.251***	-1.953***	-0.409***	4.363
	Group 2-9	value	0.914	9.097	1.623	5.267
		Obs.	5,113	5,112	5,112	5,109
	Group 1	value	0.710	7.392	1.609	0.476
		Obs.	644	644	644	643
	(Group 1) – (Group 2-9)		-0.204***	-1.706***	-0.014	-4.792
$\mathrm{EM2}_t * \mathrm{MA}_t$	Group 1-8	value	0.854	8.690	1.550	0.578
		Obs.	5,153	5,152	5,152	5,149
	Group 9	value	1.228	10.778	2.217	39.801
		Obs.	611	611	611	609
	(Group 1-8)-(Group 9)		-0.374***	-2.088***	-0.667***	-39.223***
	Group 2-9	value	0.921	9.129	1.657	5.250
		Obs.	5,125	5,124	5,124	5,119
	Group 1	value	0.677	7.170	1.329	0.535
		Obs.	639	639	639	639
	(Group 1) – (Group 2-9)		-0.244***	-1.959***	-0.329***	-4.715

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

3.7.2 Baseline analysis of factors affecting future performance of banks

We then conduct OLS regressions to further control for the effects from banks' additional attributes towards the impact of EM, BE and MA on their future performance. Table 17 reports the correlation of variables involved in our analysis. The nature log of assets (Ln(assets)) and nature log of deposits (Ln(deposits)) for sample banks are highly correlated (0.974***). Also, Ln(deposits) generates lower collinearity with other control variables than Ln(assets). Therefore, we retain Ln(deposits) as one of our control variables instead of Ln(assets) to capture bank size. In Table 17, the correlation between BE and MA is 66.7% and is significant at the 10% level. This result suggests that BE and MA are highly associated as expected, thus we do not estimate them simultaneously in a model. Correlations among all other variables are overall under 36%, which means that, theoretically, our regressions are unlikely to suffer from collinearity issues.

Table 18 reports results from our baseline analysis using equation (26) and equation (27). The results show that EM_dum has a negative impact on future bank performance, whilst BE_dum and MA_dum have positive impacts on future bank performance in all of our models. However, the association between EM_dum and future bank profitability (PM) is barely statistically significant at a 5% level, which is consistent with a finding from Beaver and Engel (1996) that EM is not linearly associated with banks' future net income. Similar significance concerns are also shown by the association between BE_dum (or MA_dum) and future bank asset quality (AQ). These results are consistent with our findings in the univariate tests that EM, BE and MA, individually, can hardly fully capture future bank performance. Banks' profitability (ROA) is captured significantly and negatively affecting their asset quality (at the 1% level), suggesting that profitable banks are generally "aggressive", they may engage in riskier business than their peers. Moreover, the coefficients of federal fund interest rate growth (FRG) are found to be significantly positive (at the 1% level), and the net charge-offs (Charge-offs) is found to have a significant negative association with banks' profitability (at the 1% level) in all our models.

Table 19 represents analysis results of regressions based on interacted variables. The results present that EMBE1_group9, EMBE2_group9, EMMA1_group9, and EMMA2_group9 have positive coefficients in all models, and majority of the coefficients are statistically significant. In contrast, EMBE1_group1, EMBE2_group1, EMMA1_group1, and EMMA2_group1 are found to have negative coefficients in all of our models (at the 10% level or better), and the coefficients are significant (at the 10% level or better) except the EMMA2_group1's coefficient on PM1. These results demonstrate that banks with superior AMB have better post-one-year profitability and asset quality than other banks, while banks with poor AMB underperform their peers in the next fiscal year. These findings highly fit our expectations, and are consistent with our Hypothesis 1. The coefficients of federal rate growth, net charge-offs and ROA, and the dynamic impacts are consistent with the results obtained from Table 18.

We further conduct t-tests on the coefficient differences of our main variables of interests based on EM1 and EM2, to investigate whether EM1 and EM2 based indicators are independent and provide distinct impacts on future bank performance. We test the coefficient differences between (1) EMBE1_group9 and EMBE2_group9, (2) EMBE1_group1 and EMBE2_group1, (3) EMMA1_group9 and EMMA2_group9, (4) EMMA1_group1 and EMMA2_group1. Our t-test results suggest that EM1 and EM2 based indicators can explain future bank performance differently.

Table 17 Correlation Matrix

This table presents the correlation coefficients between variables included in the empirical analysis. The variable definitions are presented in the Appendix B.

	$Ln(assets$	$Ln(deposit$	FRG_{t+1}	HHI_{t+1}	$NPLER_t$	$LAWF_t$	$Charge - offs_t$	ROA_{t+}	$LATA_{t-}$	$EM1_t$	$EM2_t$	BE_t	MA_t
$Ln(assets)$	1.000												
$Ln(deposit$	0.974***	1.000											
FRG_{t+1}	-0.077***	-0.078***	1.000										
HHI_{t+1}	0.355***	0.340***	-0.003	1.000									
$NPLER_{t+1}$	0.010	0.016	-0.003	-0.001	1.000								
$LAWF_{t+1}$	0.012	0.012	-0.010	-0.004	-0.006	1.000							
$Charge - offs_{t+1}$	0.040***	0.035***	0.010***	0.019*	0.047***	-0.005	1.000						
ROA_{t+1}	-0.015	-0.046***	0.008	0.001	-0.155***	-0.120***	0.159***	1.000					
$LATA_{t+1}$	0.129***	0.083***	-0.014	0.289***	0.001	0.098***	0.022*	0.061***	1.000				
$EM1_t$	-0.003	0.005	0.000	0.010	-0.018	0.008	0.066***	0.115***	0.016	1.000			
$EM2_t$	0.002	-0.002	0.000	-0.014	-0.013	0.002	-0.067***	-0.018	-0.018	0.401***	1.000		
BE_t	0.055***	0.018	0.208***	-0.043***	-0.056***	0.024*	0.015	0.216***	-0.033***	0.027**	0.030**	1.000	
MA_t	-0.039***	-0.066***	-0.009	-0.124***	-0.019	-0.033**	0.037***	0.246***	-0.120***	0.026*	0.004	0.667***	1.000

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

Table 18 Earnings management (EM), bank efficiency (BE), managerial ability (MA) and future bank performance

This table reports results from Ordinary Least Square (OLS) regressions based on EM, BE and MA dummies. The dependent variables are future bank performances, and are measured by profitability (PM) and asset quality (AQ) of the year following the base year, respectively. The measure PM comprises PM1 and PM2, where PM1 is the ratio of net income to total assets, and PM2 is the ratio of post-tax profit to total equity. The measure AQ comprises AQ1 and AQ2, where AQ1 is the ratio of reserve for impaired loans to gross loans, and AQ2 is the ratio of loan loss provisions to total loans. EM_dum, BE_dum and MA_dum are our main variables of interest in this table, and they are defined as dummies equals to one for banks belonging to the corresponding highest tertile group (Group a3), equals zero for banks belonging to the lowest tertile group (Group a1) in the base year, respectively. Note that EM is measured by the negative value of discretionary loan loss provisions (EM1) and by the negative value of discretionary loan loss reserves (EM2). Control variables are measured in the year following the based year and their definitions are presented in Appendix B. Firm and year effects are fixed and robust errors are controlled in all models.

	$PM1_{t+1}$				$PM2_{t+1}$				$AQ1_{t+1}$				$AQ2_{t+1}$			
$EM1\_dum_t$	-0.049	-0.076*			-0.762*	-0.895***			-0.107***	-0.101***			-0.205***	-0.183***		
$EM2\_dum_t$			-0.051	-0.037			-0.629*	-0.397			-0.194**	-0.204**			-0.130***	-0.135***
BE_dum_t	0.212***		0.185***		2.283***		1.926**		0.019		0.027		0.108		0.131**	
MA_dum_t		0.157***		0.088*		1.525***		0.945**		0.022		0.039		0.044		0.099*
$Ln(deposits)_{t+1}$	-0.020	0.086	-0.001	0.112**	-0.507	0.551	-0.242	0.907**	0.044	0.062	0.039	0.034	0.093*	0.156***	0.097**	0.125***
FRG_{t+1}	0.002***	0.002***	0.002***	0.002***	0.032***	0.030***	0.030***	0.027***	0.002***	0.002***	0.001**	0.002***	0.002***	0.003***	0.002***	0.002***
HHI_{t+1}	0.0003*	0.0001	0.0002	0.0001	0.005**	0.002*	0.004**	0.003**	0.0002	0.0001	0.0001	0.0002	0.0003*	0.0003**	0.0003	0.000
$NPLER_{t+1}$	-0.009***	-0.0002	-0.010***	-0.013***	-0.144***	-0.007	-0.163***	-0.167***	0.010***	0.001	0.013***	0.018***	0.014***	0.003	0.016***	0.021***
$LAWF_{t+1}$	0.0000***	0.0000	0.0000	0.0000	0.00001***	0.0000	0.00001**	0.000	0.0001***	-0.0001	0.0000	-0.0001	0.000	0.0000	0.0000	0.000
$Charge-offs_{t+1}$	-0.439***	-0.380***	-0.463***	-0.363***	-4.268***	-3.090***	-4.907***	-3.207***								
ROA_{t+1}									-0.133***	-0.135***	-0.107***	-0.084**	-0.389***	-0.365***	-0.355***	-0.313***
$LATA_{t+1}$									0.020*	0.024	0.021*	0.027	0.018	0.006	0.017	0.006
$PM1_t$	0.120*	0.177**	0.177**	0.225***												
$PM2_t$					0.124	0.252***	0.162	0.256***								
$AQ1_t$									0.501***	0.533***	0.482***	0.495***				
$AQ2_t$													0.087	0.095	0.091	0.087
Constant	1.252	-1.071	0.828	-1.522	19.555	-4.992	13.755	-11.366	-0.206	-0.600	-0.045	-0.042	-1.445	-2.757***	-1.628*	-2.305***
R-square	0.321	0.293	0.353	0.317	0.413	0.416	0.425	0.418	0.843	0.882	0.831	0.866	0.410	0.377	0.405	0.400
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obs.	2,386	1,940	2,348	1,934	2,386	1,940	2,348	1,934	2,392	1,945	2,352	1,937	2,391	1,945	2,350	1,936
Fixed firm effect	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed year effect	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Robust error	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

Table 19 Accounting managerial behaviour (AMB) and future bank performance

This table reports results from Ordinary Least Square (OLS) regressions based on AMB indicators. The dependent variables are future bank performances, and are measured by profitability (PM) and asset quality (AQ) of the year following the base year, respectively. The measure PM comprises PM1 and PM2, where PM1 is the ratio of net income to total assets, and PM2 is the ratio of post-tax profit to total equity. The measure AQ comprises AQ1 and AQ2, where AQ1 is the ratio of reserve for impaired loans to gross loans, and AQ2 is the ratio of loan loss provisions to total loans. AMB indicators are interacted tertile groups of earnings management (EM) and bank efficiency (BE) (or managerial ability (MA)) and the group structure can be found in Graph 2. Note that EM is measured by the negative value of discretionary loan loss provisions (EM1) and by the negative value of discretionary loan loss reserves (EM2). Our main interests lie in the group 1 and group 9 of AMB indicators, where group 1 represents banks that are in the combined aggressive EM tertile and the lowest BE (or MA) tertile, and group 9 represents banks that are in the combined conservative EM tertile and the highest BE (or MA) tertile, based on the AMB measured in the base year. $\mathrm{EMBE1\_group9}_t$, $\mathrm{EMBE1\_group1}_t$, $\mathrm{EMBE2\_group9}_t$, $\mathrm{EMBE2\_group1}_t$, $\mathrm{EMMA1\_group9}_t$, $\mathrm{EMMA1\_group1}_t$, $\mathrm{EMMA2\_group9}_t$ and $\mathrm{EMMA2\_group1}_t$ represent AMB indicators. EMBE_group9 is valued one if the combined EM and BE metric lies in group 9, zero otherwise, and EMBE_group1 is valued one if the combined EM and BE metric lies in group 1, zero otherwise. Similarly, EMMA_group9 is valued one if the combined EM and MA metric lies in group 9, zero otherwise, and EMMA_group1 is valued one if the combined EM and MA metric lies in group 1, zero otherwise. Control variables are measured in the year following the based year and their definitions are presented in Appendix B. Firm and year effects are fixed and robust errors are controlled in all models.

	$\mathrm{PM1}_{t+1}$				$\mathrm{PM2}_{t+1}$				$\mathrm{AQ1}_{t+1}$				$\mathrm{AQ2}_{t+1}$			
$\mathrm{EMBE1\_group9}_t$	0.084*				1.052**				0.067*				0.142***			
$\mathrm{EMBE1\_group1}_t$	-0.145***				-1.610***				-0.059**				-0.143***			
$\mathrm{EMBE2\_group9}_t$		0.068				0.675				0.118**				0.124**		
$\mathrm{EMBE2\_group1}_t$		-0.120***				-1.307***				-0.064*				-0.060*		
$\mathrm{EMMA1\_group9}_t$			0.079**				0.826**				0.077**				0.103**	
$\mathrm{EMMA1\_group1}_t$			-0.089***				-1.106***				-0.075***				-0.147***	
$\mathrm{EMMA2\_group9}_t$				0.073				0.734*				0.133**				0.091
$\mathrm{EMMA2\_group1}_t$				-0.039				-0.567*				-0.073**				-0.082***
$\mathrm{Ln(deposits)}_{t+1}$	-0.035	-0.031	0.033	0.035	-0.505	-0.463	0.309	0.323	0.024	0.025	0.036*	0.039*	0.087**	0.091**	0.131***	0.133***
FRG_{t+1}	0.001**	0.001**	0.001***	0.001***	0.022***	0.023***	0.025***	0.025***	0.001***	0.001***	0.001***	0.001***	0.002***	0.002***	0.002***	0.002***
HHI_{t+1}	0.0002*	0.0002*	0.0001	0.0001	0.003***	0.003***	0.002*	0.002*	0.0002	0.0002	0.0002	0.0002	0.0002*	0.0003	0.0002	0.0003
NPLER_{t+1}	-0.002	-0.002	-0.001	-0.001	-0.029	-0.030	-0.019	-0.020	0.002	0.002	0.001	0.001	0.002	0.002	0.001	0.001
LAWF_{t+1}	0.0000	0.0000	0.0000	0.0000	0.0004	0.0004	0.0004	0.0003	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	0.0000	0.0000
$\mathrm{Charge-offs}_{t+1}$	-0.520***	-0.519***	-0.448***	-0.447***	-5.255***	-5.238***	-4.431***	-4.420***								
ROA_{t+1}									-0.187***	-0.187***	-0.174***	-0.174***	-0.489***	-0.486***	-0.447***	-0.444***
LATA_{t+1}									0.030**	0.030**	0.026*	0.027*	0.022	0.022	0.000	-0.001
$\mathrm{PM1}_t$	0.173***	0.174***	0.193***	0.194***												
$\mathrm{PM2}_t$					0.207***	0.209***	0.205**	0.206***								
$\mathrm{AQ1}_t$									0.547***	0.542***	0.550***	0.544***				
$\mathrm{AQ2}_t$													0.137*	0.140*	0.133	0.137
Constant	1.665	1.576	0.145	0.113	19.764	18.797	1.699	1.316	0.201	0.177	-0.086	-0.139	-1.205	-1.309	-2.191***	-2.250***
R-square	0.330	0.332	0.356	0.355	0.399	0.401	0.407	0.405	0.835	0.832	0.854	0.850	0.448	0.443	0.440	0.435
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obs.	5,491	5,493	4,556	4,558	5,490	5,492	4,555	4,557	5,499	5,501	4,563	4,565	5,497	5,498	4,562	4,563
Fixed firm effect	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed year effect	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Robust error	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

3.7.3 Robustness checks and sensitive tests

This section uses various models and specifications to test the sensitivity and robustness of our baseline analysis results.

Sensitivity to global financial crisis and Sarbanes-Oxley Act

Sarbanes-Oxley Act (SOX) is implemented in October 2002 to reinforce the consequences of misleading accounting errors and fraudulent practices, which could potentially affect banks' efficiency and their EM activities. Therefore, SOX could affect the impact of AMB on future bank performance. We address this concern by including a SOX dummy (SOX) in our baseline models (equation (28) and (29)). We define SOX equals one for the period 2002 to 2017, zero otherwise.

Additionally, our sample period also contains the period of the global financial crisis (GFC). GFC has a profound impact on the U.S. banking industry due to the increase of default risks and the decrease in credit release to the public. GFC (2007-2009) has also been found to affect banks' decisions on EM practices (Alali and Jaggi, 2011; Alali and Jaggi, 2011; El Sood, 2012), which may impact the association between AMB and future bank performance. We test the sensitivity of our model to GFC by introducing a dummy ($\mathrm{GFC}_{2007-2009}$) in our baseline models. The dummy is defined as one for the GFC period (2007-2009), zero otherwise. We test the sensitivity of our results to SOX and GFC in the same regression model to save space.

The results are reported in Table 20, where control variables are included in all models but only our main variables of interest, SOX, and $\mathrm{GFC}_{2007-2009}$ are reported due to the space limitation. The results are highly consistent with the results from Table 19 that banks with superior AMB (Group 9) outperform other banks in the following fiscal year, while banks with poor AMB (Group 1) underperform their peers in the next year. The results suggest that our initial findings are not sensitive to the GFC impacts and the SOX act.

Table 20 Accounting managerial behaviour (AMB) and future bank performance controlling for GFC and SOX

This table reports results from Ordinary Least Square (OLS) regressions based on AMB indicators with controls for global financial crisis (GFC) and Sarbanes-Oxley Act (SOX) impacts. The dependent variables are future bank performances, and are measured by profitability (PM) and asset quality (AQ) of the year following the base year, respectively. The measure PM comprises PM1 and PM2, where PM1 is the ratio of net income to total assets, and PM2 is the ratio of post-tax profit to total equity. The measure AQ comprises AQ1 and AQ2, where AQ1 is the ratio of reserve for impaired loans to gross loans, and AQ2 is the ratio of loan loss provisions to total loans. AMB indicators are interacted tertile groups of earnings management (EM) and bank efficiency (BE) (or managerial ability (MA)) and the group structure can be found in Graph 2. Note that EM is measured by the negative value of discretionary loan loss provisions (EM1) and by the negative value of discretionary loan loss reserves (EM2). Our main interests lie in the group 1 and group 9 of AMB indicators, where group 1 represents banks that are in the combined aggressive EM tertile and the lowest BE (or MA) tertile, and group 9 represents banks that are in the combined conservative EM tertile and the highest BE (or MA) tertile, based on the AMB measured in the base year. $EMBE1\_group9_t$, $EMBE1\_group1_t$, $EMBE2\_group9_t$, $EMBE2\_group1_t$, $EMMA1\_group9_t$, $EMMA1\_group1_t$, $EMMA2\_group9_t$ and $EMMA2\_group1_t$ represent AMB indicators. EMBE_group9 is valued one if the combined EM and BE metric lies in group 9, zero otherwise, and EMBE_group1 is valued one if the combined EM and BE metric lies in group 1, zero otherwise. Similarly, EMMA_group9 is valued one if the combined EM and MA metric lies in group 9, zero otherwise, and EMMA_group1 is valued one if the combined EM and MA metric lies in group 1, zero otherwise. The GFC dummy ($GFC_{2007-2009}$) is set to one during the period 2007 to 2009, zero otherwise; and the SOX dummy is defined as one for years since 2002, zero otherwise. Control variables are measured in the year following the based year and their definitions are presented in Appendix B, however, the coefficients of control variables are not reported due to the space limitation. Firm and year effects are fixed and robust errors are controlled in all models.

	$PM1_{t+1}$				$PM2_{t+1}$				$AQ1_{t+1}$				$AQ2_{t+1}$			
$EMBE1\_group9_t$	0.084*				1.052**				0.067*				0.142***			
$EMBE1\_group1_t$	-0.145***				-1.610***				-0.059**				-0.143***			
$EMBE2\_group9_t$		0.068				0.675				0.118**				0.124**		
$EMBE2\_group1_t$		-0.120***				-1.307***				-0.064*				-0.069*		
$EMMA1\_group9_t$			0.079**				0.826**				0.077**				0.103**	
$EMMA1\_group1_t$			-0.089***				-1.106***				-0.075***				-0.147***	
$EMMA2\_group9_t$				0.073				0.734*				0.133**				0.091
$EMMA2\_group1_t$				-0.039				-0.567*				-0.073**				-0.082***
$GFC_{2007-2009}$	0.254**	0.254**	0.203	0.215*	3.171**	3.134**	2.379*	2.478*	0.319**	0.327**	0.306**	0.320**	0.486**	0.483**	0.527**	0.522**
SOX	-0.115	-0.117	-0.184	-0.209	-3.735	-3.680	-4.034*	-4.257*	-0.129	-0.136	-0.147	-0.166	0.053	0.051	0.038	0.033
R-square	0.330	0.332	0.356	0.355	0.399	0.401	0.407	0.405	0.835	0.832	0.854	0.850	0.448	0.443	0.440	0.435
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obs.	5,491	5,493	4,556	4,558	5,490	5,492	4,555	4,557	5,499	5,501	4,563	4,565	5,497	5,498	4,562	4,563
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed firm effect	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed year effect	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Robust error	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

We further set an additional global financial crisis dummy ($GFC_{2006-2010}$) equals one for the period of 2006 to 2010, zero otherwise. We set the additional dummy so that at least one of the following variables, (1) the base year (t), (2) the year following the base year (t+1), (3) the year prior to the based year (t-1), lie within the period of 2007 to 2009. Year t-1 is restricted because EM is extracted from LLPs and LLRs models that control for LLPs and LLPs values at year t-1. We extend the GFC periods to better control for the impacts of GFC on the association between AMB and bank performance. We then re-conduct equation (28) and (29), controlling for SOX and $GFC_{2006-2010}$. The results are comparable with the ones reported in Table 20, indicating the robustness of our previous findings.

Table 21 Average accounting managerial behaviour (AMB) and future bank performance

This table reports results from Ordinary Least Square (OLS) regressions based on three-year average AMB indicators. The dependent variables are future bank performances, and are measured by profitability (PM) and asset quality (AQ) of the year following the base year, respectively. The measure PM comprises PM1 and PM2, where PM1 is the ratio of net income to total assets, and PM2 is the ratio of post-tax profit to total equity. The measure AQ comprises AQ1 and AQ2, where AQ1 is the ratio of reserve for impaired loans to gross loans, and AQ2 is the ratio of loan loss provisions to total loans. The three-year average AMB indicators are interacted tertile groups of three-year average earnings management (EM) and three-year average bank efficiency (BE) (or managerial ability (MA)), where the three-year period comprises the base year and two years prior to the base year. Note that EM is measured by the negative value of discretionary loan loss provisions (EM1) and by the negative value of discretionary loan loss reserves (EM2). Our main interests lie in the group 1 and group 9 of the three-year average AMB indicators, where group 1 represents banks that are in the combined aggressive three-year average EM tertile and the lowest three-year average BE (or MA) tertile, and group 9 represents banks that are in the combined conservative three-year average EM tertile and the highest three-year average BE (or MA) tertile. $\mathrm{EMBE1\_group9}_{t-2,t}$, $\mathrm{EMBE1\_group1}_{t-2,t}$, $\mathrm{EMBE2\_group9}_{t-2,t}$, $\mathrm{EMBE2\_group1}_{t-2,t}$, $\mathrm{EMMA1\_group9}_{t-2,t}$, $\mathrm{EMMA1\_group1}_{t-2,t}$, $\mathrm{EMMA2\_group9}_{t-2,t}$ and $\mathrm{EMMA2\_group1}_{t-2,t}$ represent three-year average AMB indicators. . EMBE_group9 is valued one if the combined EM and BE metric lies in group 9, zero otherwise, and EMBE_group1 is valued one if the combined EM and BE metric lies in group 1, zero otherwise. Similarly, EMMA_group9 is valued one if the combined EM and MA metric lies in group 9, zero otherwise, and EMMA_group1 is valued one if the combined EM and MA metric lies in group 1, zero otherwise. Control variables are measured in the year following the based year and their definitions are presented in Appendix B, however, the coefficients of control variables are not reported due to the space limitation. Firm and year effects are fixed and robust errors are controlled in all models.

	$PM1_{t+1}$				$PM2_{t+1}$				$AQ1_{t+1}$				$AQ2_{t+1}$			
$EMBE1\_group9_{t-2,t}$	0.071				0.807				0.110**				0.138**			
$EMBE1\_group1_{t-2,t}$	-0.076**				-1.005**				-0.069***				-0.091***			
$EMBE2\_group9_{t-2,t}$		0.058				0.534				0.052				0.096*		
$EMBE2\_group1_{t-2,t}$		-0.052				-0.864**				-0.029				-0.069**		
$EMMA1\_group9_{t-2,t}$			0.132**				1.066**				0.096**				0.110*	
$EMMA1\_group1_{t-2,t}$			-0.098***				-0.977***				-0.056**				-0.086**	
$EMMA2\_group9_{t-2,t}$				0.120**				0.993**				0.037				0.044
$EMMA2\_group1_{t-2,t}$				-0.053				-0.440				-0.021				-0.038
R-square	0.336	0.337	0.348	0.346	0.411	0.413	0.395	0.392	0.864	0.860	0.882	0.880	0.505	0.496	0.490	0.482
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obs.	5,210	5,210	4,347	4,347	5,206	5,206	4,344	4,344	5,223	5,223	4,358	4,358	5,219	5,219	4,356	4,356
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed firm effect	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed year effect	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Robust error	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

Business-cycle effects

This chapter aims to study the signalling role of AMB on future bank performance. A favourable signal is expected to be stable and reliable with time, therefore, in this section, we investigate whether the signalling role of AMB still exists after considering business-cycle effects. For this purpose, we substitute year t's EM, BE and MA indicators using their average value from year t-2 to year t, in our pre-designed models (equation (28) and (29)). The idea of taking three-year average is inspired by Shen and Huang (2013) and Cohen, Cornett, Marcus and Tehranian (2014). We generate groups (Group a1, Group a2 and Group a3) based on the three-year average value of EM, BE and MA instead of the single-year value discussed in the empirical analysis design section, and use these new groups to generate interacted groups. The group construction is similar with the ones shown in Graph 1 and Graph 2. We expect those three-year-average AMB indicators have analogous performance compared to the one-year AMB indicators from our baseline analysis.

Table 21 represents results from fixed-effect OLS models using interacted three-year-average AMB dummies. Control variables are included accordingly in all of the reported models, but only the main variables of interest are reported due to the space limitation. The results show that EMBE1_group9, EMBE2_group9, EMMA1_group9, and EMMA2_group9 have significantly positive coefficients in the majority of the models, and EMBE1_group1, EMBE2_group1, EMMA1_group1 and EMMA2_group1 have significantly negative coefficients in the most of our models. The results are consistent with our initial findings that banks with superior AMB have better future performance than their peer banks, whereas banks with poor AMB underperform their peers in the following fiscal year. Our findings suggest that the one-year AMB indicators have similar signalling power as the three-year-average AMB indicators, which means that AMB can predict future bank performance after considering business cycle effects. The results also imply that using one-year AMB to signal future bank performance is more efficient than using the three-year-average AMB because they have similar signalling effect.

Endogeneity

It is possible that AMB indicators are endogenous. Some attributes, that are hard to be quantized such as environmental uncertainties, could affect the profitability and asset quality of U.S. commercial banks through our AMB indicators. Moreover, we use dynamic panel models in our baseline analysis, thus the lagged dependent variables could potentially be endogenous as well. This means that the lag value of PM or AQ is likely to be associated with analysis residuals, if some factors could affect the bank performance via influencing their profitability or asset quality at the previous year.

We first test the endogenous possibility of AMB indicators and the lagged value of PM and AQ using the extended Durbin-Wu-Hausman tests for panel data. The results suggest that our main variables of interest (i.e. AMB proxies) and the first lag of AQ are exogenous in our models, when given exogenous and efficient instruments. Therefore, this section is only used to address the endogenous problem of PM's dynamic term.

Selecting and modelling reasonable instruments is always a tough process in designing dynamic models. Additionally, our dataset has the specifications of small amount of sample periods with a large cross-sectional panel setting. Considering these two facts, we adopt a two-step system Generalised Method of Moments model (GMM) to control for the endogenous issue instead of the Two-stage Least Squared model (2SLS). We choose PM's 4th (or 5th) and deeper lags as instruments for PM models, after adjusting the instruments based on the effectiveness and the over-identifying restrictions using Hansen's J test. We use two-step GMM to allow the standard covariance matrix to be robust to panel-specific autocorrelation and heteroscedasticity, and we use robust errors to correct the downward bias of the standard error. System GMM automatically controls for time-invariant factors and we include year dummies to eliminate individual-invariant effects. We further apply the forward orthogonal deviations transform of instruments instead of the first difference transformation to eliminate the gaps in our unbalanced panel.

The results are presented in Table 22, where control variables are included in all models but only our main variables of interest are reported due to the space limitation. The Chi-square indicators from Hansen J-tests are insignificant in all of our models, which indicates that our lagged instruments are exogenous and are not over-identifying our endogenous variables. In addition, the coefficients of EMBE1_group9, EMBE2_group9, EMMA1_group9 and EMMA2_group9 are positive and mostly significant, and the coefficients of EMBE1_group1, EMBE2_group1, EMMA1_group1 and EMMA2_group1 are significantly negative in the majority of our models. These results are consistent with our Hypothesis 1 and our previous findings in Table 19 that banks' AMB affects their performance in the following year, which means our previous findings stand after controlling for potential endogenous issues.

Table 22 Accounting managerial behaviour (AMB) and future bank performance with endogenous controls

This table reports results from two-step system General Method of Moment (GMM) models. We only find endogeneity in the lag value of profitability (PM) in our baseline analyses, thus GMM is only applied to PM models.
The dependent variables are future bank performances measured by profitability (PM). The measure PM comprises PM1 and PM2, where PM1 is the ratio of net income to total assets, and PM2 is the ratio of post-tax profit to total equity. AMB indicators are interacted tertile groups of earnings management (EM) and bank efficiency (BE) (or managerial ability (MA)) and the group structure can be found in Graph 2. Note that EM is measured by the negative value of discretionary loan loss provisions (EM1) and by the negative value of discretionary loan loss reserves (EM2). Our main interests lie in the group 1 and group 9 of AMB indicators, where group 1 represents banks that are in the combined aggressive EM tertile and the lowest BE (or MA) tertile, and group 9 represents banks that are in the combined conservative EM tertile and the highest BE (or MA) tertile, based on the AMB measured in the base year. $EMBE1\_group9_t$, $EMBE1\_group1_t$, $EMBE2\_group9_t$, $EMBE2\_group1_t$, $EMMA1\_group9_t$, $EMMA1\_group1_t$, $EMMA2\_group9_t$ and $EMMA2\_group1_t$ represent AMB indicators EMBE_group9 is valued one if the combined EM and BE metric lies in group 9, zero otherwise, and EMBE_group1 is valued one if the combined EM and BE metric lies in group 1, zero otherwise. Similarly, EMMA_group9 is valued one if the combined EM and MA metric lies in group 9, zero otherwise, and EMMA_group1 is valued one if the combined EM and MA metric lies in group 1, zero otherwise. We choose instrumental lag variables based on Hansen J tests to avoid over-identification issues. Overall, 4[th] or 5[th] and deeper lags of dependent variables are used as instruments. Control variables are measured in the year following the based year and their definitions are presented in Appendix B, however, the coefficients of control variables are not reported due to the space limitation. Firm and year effects are fixed and robust errors are controlled in all models.

	$PM1_{t+1}$				$PM2_{t+1}$			
$EMBE1\_group9_t$	0.074				1.287**			
Endogeneous	no				no			
$EMBE1\_group1_t$	-0.383*				-2.500*			
Endogeneous	no				no			
$EMBE2\_group9_t$		0.113				0.756		
Endogeneous		no				Yes		
$EMBE2\_group1_t$		-0.157***				-1.861***		
Endogeneous		no				no		
$EMMA1\_group9_t$			0.108**				1.006***	
Endogeneous			no				no	
$EMMA1\_group1_t$			-0.051*				-0.770***	
Endogeneous			no				no	
$EMMA2\_group9_t$				0.124**				1.021**
Endogeneous				no				no
$EMMA2\_group1_t$				-0.027				-0.721**
Endogeneous				no				no
$PM1_t$	0.177	0.270	0.326**	0.315**				
Endogeneous	yes	yes	yes	yes				
$PM2_t$					0.148	0.112	0.194	0.192
Endogeneous					yes	yes	Yes	Yes
Take instrumental lags start from	5th	5th	4th	4th	5th	4th	4th	5th
F-statistic	26.13***	27.64***	26.82***	29.20***	27.90***	23.18***	19.51***	18.39***
AR(2) z-score	0.65	0.96	1.65*	1.64	0.12	-0.01	0.42	0.46
Hansen J test chi2	86.89	94.03	100.49	99.52	88.36	104.35	98.79	92.12
Obs.	5,491	5,493	4,556	4,558	5,490	5,492	4,555	4,557
Control variables	yes	yes	yes	yes	yes	yes	yes	yes
Fixed firm& year effect	yes	yes	yes	yes	yes	yes	yes	yes
Robust error	yes	yes	yes	yes	yes	yes	yes	yes

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

Table 23 Accounting managerial behaviour (AMB) and future bank performance controlling for sample sensitivity and sample selection bias

This table reports results from Ordinary Least Square (OLS) regressions based on AMB indicators with more restricted sample groups to eliminate potential sample selection bias. We test the sensitivity of sample distribution by re-structuring EM, BE and MA into four sub-groups, respectively. We then assign banks that belong to the top group of BE (or MA) as well as the lowest group of EM to group 9, and assign banks that belong to the lowest group of BE (or MA) as well as the top group of EM to group 1. We further control for the sample bias by matching banks from control groups with banks in our test groups by a propensity score matching (PSM) method. We use the PSM approach to match control banks based on bank age, return on assets, deposits and liquidity ratio for group 9 and group 1 of each AMB variables. The dependent variables are future bank performances, and are measured by profitability (PM) and asset quality (AQ) of the year following the base year, respectively. The measure PM comprises PM1 and PM2, where PM1 is the ratio of net income to total assets, and PM2 is the ratio of post-tax profit to total equity. The measure AQ comprises AQ1 and AQ2, where AQ1 is the ratio of reserve for impaired loans to gross loans, and AQ2 is the ratio of loan loss provisions to total loans. AMB indicators are interacted tertile groups of earnings management (EM) and bank efficiency (BE) (or managerial ability (MA)) and the group structure can be found in Graph 2. Note that EM is measured by the negative value of discretionary loan loss provisions (EM1) and by the negative value of discretionary loan loss reserves (EM2). Our main interests lie in the group 1 and group 9 of AMB indicators, where group 1 represents banks that are in the combined aggressive EM tertile and the lowest BE (or MA) tertile, and group 9 represents banks that are in the combined conservative EM tertile and the highest BE (or MA) tertile, based on the AMB measured in the base year. $EMBE1\_group9_t$, $EMBE1\_group1_t$, $EMBE2\_group9_t$, $EMBE2\_group1_t$, $EMMA1\_group9_t$, $EMMA1\_group1_t$, $EMMA2\_group9_t$ and $EMMA2\_group1_t$ represent AMB indicators. EMBE_group9 is valued one if the combined EM and BE metric lies in group 9, zero otherwise, and EMBE_group1 is valued one if the combined EM and BE metric lies in group 1, zero otherwise. Similarly, EMMA_group9 is valued one if the combined EM and MA metric lies in group 9, zero otherwise, and EMMA_group1 is valued one if the combined EM and MA metric lies in group 1, zero otherwise. We use propensity scores to match control banks for Group 9 and Group 1 respectively, because group 9 and group 1 of the same AMB indicator would most likely match with different control banks. Results of group 9 and group 1 are reported in the same column to save spaces. Control variables are measured in the year following the based year and their definitions are presented in Appendix B, however, the coefficients of control variables are not reported due to the space limitation. Firm and year effects are fixed and robust errors are controlled in all models.

	$PM1_{t+1}$				$PM2_{t+1}$				$AQ1_{t+1}$				$AQ2_{t+1}$			
$EMBE1\_group9_t$	0.200*				1.187**				0.088*				0.180***			
$EMBE1\_group1_t$	-0.117***				-1.800***				-0.055				-0.071			
$EMBE2\_group9_t$		0.121				0.594				0.081				0.079		
$EMBE2\_group1_t$		-0.114**				-2.053**				-0.060*				-0.108**		
$EMMA1\_group9_t$			0.077*				0.505				0.006				-0.009	
$EMMA1\_group1_t$			-0.095**				-1.070**				-0.090***				-0.132***	
$EMMA2\_group9_t$				0.175**				1.189*				0.171***				0.118*
$EMMA2\_group1_t$				-0.036				-0.451				-0.030				-0.099**
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed firm effect	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed year effect	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Robust error	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

* Statistically significant at 10% level.

** Statistically significant at 5% level.

*** Statistically significant at 1% level.

Sample sensitivity and selection bias

In our previous tests, we divide EM, BE and MA into three equal groups, respectively, which could potentially dominate our analysis results. Therefore, in this section, we test the sensitivity of our findings to the group distributions by re-structuring EM, BE and MA into four sub-groups, respectively. We then assign banks that belong to the top BE (or MA) group and the lowest EM group to AMB Group 9, and assign banks that belong to the lowest BE (or MA) group as well as the top EM group to AMB Group 1. As we have assumed before, we expect banks that belong to AMB Group 9 (superior AMB) outperform their peers, whilst banks that belong to AMB Group 1 (poor AMB) underperform their peers in the next fiscal year.

Previously, we compare future performance of banks in AMB Group 1 (or Group 9) with banks in the rest corresponding groups. For instance, we compare banks' future performance of EMBE1 Group 1 with EMBE1 Group 2-9. However, banks can be self-selected into a certain AMB group due to their attributes such as bank age, other than EM, BE and MA. Therefore, this section is further designed to eliminate the self-selection bias in our model by matching banks in Group 1 (or Group 9) of AMB indicators with the rest banks using a Propensity Score Matching (PSM) approach. The PSM method is conducted by year.

The number of banks in test groups (i.e. group1 and group9) in this section is smaller than our initially designed test groups, thus the propensity score matching approach is able to match corresponding control banks from a larger sample group. This means that testing the sample selection bias together with the sample sensitivity is likely to increase the effectiveness of our PSM approach. We treat the recently defined Group 1 and Group 9 as test groups and match control groups for each test group using propensity scores based on bank age, return on assets, deposits, and liquidity assets to total wholesale funding ratio in each fiscal year. For each AMB indicator, banks in Group 9 and Group 1 of that indicator can be matched with different control banks. Therefore, in this section, we replicate equation (28) and (29), but run regressions for dummy variables of Group 9 and Group1 for each AMB indicator, respectively. This may lead to some minor differences in results compared with the results reported in Table 19.

We report the results in Table 23, where control variables are included in all models but only our main variables of interest are reported due to the space limitation. In table 23, we observe overall positive and significant coefficients for Group 9 dummies and significantly negative coefficients for Group 1 dummies. These results suggest that our initial finding that banks' AMB affects their future performance stand after controlling for potential self-selection bias and sample sensitivity.

Dynamic/ Row effect of AMB

It is likely that AMB indicators may have a dynamic impact, which means that year t+1's bank performance may be affected by year t's AMB because year t's AMB is highly and positively correlated with year t+1's AMB. To address this concern, we test the correlation coefficients of year t's AMB on year t+1's AMB. The results show that the coefficients of all AMB indicators (including group 9 and group 1 dummies) are around 0.18 (maximum: 0.21, minimum: 0.16). These results imply that year t's AMB is not highly relevant to year t+1's AMB.

Then, we recall equation (28) and (29) with additional indicators of year t+1's AMB proxies to investigate whether our previous findings are sensitive to the dynamic impacts caused by AMB. The results are displayed in table 24. The results show that the coefficients of year t's EMBE1_group9, EMBE2_group9, EMMA1_group9 and EMMA2_group9 are positive, while the coefficients of year t's EMBE1_group1, EMBE2_group1, EMMA1_group1 and EMMA2_group1 are negative in all of our models. Additionally, the coefficients are significant in the majority of the models. We further find that the coefficients of year t's AMB indicators as well as the significance level of these coefficients are close to the results reported in Table 19. Our results indicate that after controlling for year t+1's AMB (dynamic effects from AMB), year t's AMB still carry explanatory power towards subsequent bank performance, which fits our expectation.

3.7.4 Size effect

This section is designed to further investigate the impact power of AMB on bank performance by considering the association between bank size and bank performance. Previous studies have documented a positive association between bank size and bank performance (see Köster and Pelster, 2017; Meles, Porzio, Sampagnaro and Verdoliva, 2016; Mamatzakis and Bermpei, 2016; Bakoush, Abouarab and Wolfe, 2018). We investigate the impact of bank size on bank performance by interacting Group 9 and Group 1 dummies of AMB with the nature logarithm of bank size as our main variables of interest. These interactions are then used to model future bank performance with all of our control variables defined in equation (28) and (29). We also control for the firm-fixed effect, the year-fixed effect and clustered robust errors in all of our models.

Table 24 Accounting managerial behaviour (AMB) and future bank performance with current year effect

This table reports results from Ordinary Least Square (OLS) regressions based on AMB indicators with a control of the subsequent year's AMB. The dependent variables are future bank performances, and are measured by profitability (PM) and asset quality (AQ) of the year following the base year, respectively. The measure PM comprises PM1 and PM2, where PM1 is the ratio of net income to total assets, and PM2 is the ratio of post-tax profit to total equity. The measure AQ comprises AQ1 and AQ2, where AQ1 is the ratio of reserve for impaired loans to gross loans, and AQ2 is the ratio of loan loss provisions to total loans. AMB indicators are interacted tertile groups of earnings management (EM) and bank efficiency (BE) (or managerial ability (MA)) and the group structure can be found in Graph 2. Note that EM is measured by the negative value of discretionary loan loss provisions (EM1) and by the negative value of discretionary loan loss reserves (EM2). Our main interests lie in the group 1 and group 9 of AMB indicators at year t and year t+1, where group 1 represents banks that are in the combined aggressive EM tertile and the lowest BE (or MA) tertile, and group 9 represents banks that are in the combined conservative EM tertile and the highest BE (or MA) tertile. $\mathrm{EMBE1\_group9}_t$, $\mathrm{EMBE1\_group1}_t$, $\mathrm{EMBE2\_group9}_t$, $\mathrm{EMBE2\_group1}_t$, $\mathrm{EMMA1\_group9}_t$, $\mathrm{EMMA1\_group1}_t$, $\mathrm{EMMA2\_group9}_t$ and $\mathrm{EMMA2\_group1}_t$ represent AMB indicators. EMBE_group9 is valued one if the combined EM and BE metric lies in group 9, zero otherwise, and EMBE_group1 is valued one if the combined EM and BE metric lies in group 1, zero otherwise. Similarly, EMMA_group9 is valued one if the combined EM and MA metric lies in group 9, zero otherwise, and EMMA_group1 is valued one if the combined EM and MA metric lies in group 1, zero otherwise. Control variables are measured in the year following the based year and their definitions are presented in Appendix B. Firm and year effects are fixed and robust errors are controlled in all models.

	$\mathrm{PM1}_{t+1}$				$\mathrm{PM2}_{t+1}$				$\mathrm{AQ1}_{t+1}$				$\mathrm{AQ2}_{t+1}$			
$\mathrm{EMBE1\_group9}_t$	0.054				0.658*				0.064*				0.147***			
$\mathrm{EMBE1\_group1}_t$	-0.122***				-1.436***				-0.061**				-0.142***			
$\mathrm{EMBE1\_group9}_{t+1}$	0.097*				0.872*				0.145***				0.178***			
$\mathrm{EMBE1\_group1}_{t+1}$	-0.005				-0.005				-0.179***				-0.169***			
$\mathrm{EMBE2\_group9}_t$		0.038				0.319				0.116**				0.131**		
$\mathrm{EMBE2\_group1}_t$		-0.095**				-1.194***				-0.076**				-0.055*		
$\mathrm{EMBE2\_group9}_{t+1}$		0.098**				0.645*				0.243***				0.117**		
$\mathrm{EMBE2\_group1}_{t+1}$		0.009				0.105				-0.283***				0.005		
$\mathrm{EMMA1\_group9}_t$			0.067*				0.784**				0.085**				0.102*	
$\mathrm{EMMA1\_group1}_t$			-0.077***				-0.928***				-0.051*				-0.128***	
$\mathrm{EMMA1\_group9}_{t+1}$			0.024				0.125				0.175***				0.225***	
$\mathrm{EMMA1\_group1}_{t+1}$			0.010				0.290				-0.165***				-0.233***	
$\mathrm{EMMA2\_group9}_t$				0.060				0.690				0.140**				0.102*
$\mathrm{EMMA2\_group1}_t$				-0.038				-0.452*				-0.053				-0.068**
$\mathrm{EMMA2\_group9}_{t+1}$				0.045				0.082				0.273***				0.148***
$\mathrm{EMMA2\_group1}_{t+1}$				0.055				0.723				-0.263***				-0.065
R-square	0.331	0.332	0.366	0.365	0.409	0.411	0.457	0.455	0.839	0.828	0.858	0.845	0.441	0.426	0.457	0.441
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obs.	5,166	5,169	4,250	4,253	5,166	5,169	4,250	4,253	5,166	5,169	4,250	4,253	5,166	5,167	4,250	4,251
Fixed firm effect	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed year effect	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Robust error	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

Table 25 Accounting managerial behaviour (AMB), future bank performance and size effect

This table reports results from Ordinary Least Square (OLS) regressions to estimate the impact of AMB indicators on the association between bank sizes and bank performance. The dependent variables are future bank performances, and are measured by profitability (PM) and asset quality (AQ) of the year following the base year, respectively. The measure PM comprises PM1 and PM2, where PM1 is the ratio of net income to total assets, and PM2 is the ratio of post-tax profit to total equity. The measure AQ comprises AQ1 and AQ2, where AQ1 is the ratio of reserve for impaired loans to gross loans, and AQ2 is the ratio of loan loss provisions to total loans. AMB indicators are interacted tertile groups of earnings management (EM) and bank efficiency (BE) (or managerial ability (MA)) and the group structure can be found in Figure 2. Note that EM is measured by the negative value of discretionary loan loss provisions (EM1) and by the negative value of discretionary loan loss reserves (EM2). Our main interests lie in the interactions of group 1 and group 9 of AMB indicators with the nature logarithm of bank size, where group 1 represents banks that are in the combined aggressive EM tertile and the lowest BE (or MA) tertile, and group 9 represents banks that are in the combined conservative EM tertile and the highest BE (or MA) tertile, based on the AMB measured in the base year. $EMBE1\_group9_t$, $EMBE1\_group1_t$, $EMBE2\_group9_t$, $EMBE2\_group1_t$, $EMMA1\_group9_t$, $EMMA1\_group1_t$, $EMMA2\_group9_t$ and $EMMA2\_group1_t$ represent AMB indicators. EMBE_group9 is valued one if the combined EM and BE metric lies in group 9, zero otherwise, and EMBE_group1 is valued one if the combined EM and BE metric lies in group 1, zero otherwise. Similarly, EMMA_group9 is valued one if the combined EM and MA metric lies in group 9, zero otherwise, and EMMA_group1 is valued one if the combined EM and MA metric lies in group 1, zero otherwise. Control variables are measured in the year following the based year and their definitions are presented in Appendix B, however, the coefficients of control variables are not reported due to the space limitation. Firm and year effects are fixed and robust errors are controlled in all models.

	$PM1_{t+1}$				$PM2_{t+1}$				$AQ1_{t+1}$				$AQ2_{t+1}$			
$EMBE1\_group9_t * size_t$	0.04*				0.048**				0.003**				0.007***			
$EMBE1\_group1_t * size_t$	-0.007***				-0.073***				-0.003**				-0.007***			
$EMBE2\_group9_t * size_t$		0.003				0.032				0.006**				0.006**		
$EMBE2\_group1_t * size_t$		-0.006***				-0.060***				-0.003**				-0.003**		
$EMMA1\_group9_t * size_t$			0.004**				0.041**				0.004**				0.006**	
$EMMA1\_group1_t * size_t$			-0.004***				-0.049***				-0.004***				-0.007***	
$EMMA2\_group9_t * size_t$				0.004				0.037*				0.006**				0.005
$EMMA2\_group1_t * size_t$				-0.002				-0.024				-0.004**				-0.004**
R-square	0.330	0.332	0.357	0.355	0.399	0.401	0.407	0.405	0.835	0.832	0.854	0.850	0.449	0.443	0.441	0.436
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obs.	5,491	5,493	4,556	4,558	5,490	5,492	4,555	4,557	5,499	5,501	4,563	4,565	5,497	5,498	4.562	4,563
Fixed firm effect	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed year effect	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Robust error	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

Results are presented in Table 25, where control variables are included in all models but only our main variables of interest are reported due to the space limitation. The coefficients of the Group 9 interactions in all of our models are positive and most of them are statistically significant. This finding indicates that the larger the size, the more positive impacts that banks with superior AMB have on their future performance. In addition, the coefficients of Group 1 interactions are significantly negative in most of our models, which means that bank size has a negative impact on the future performance of banks with poor AMB. Overall, our findings in this section suggest that AMB can potentially dominate the impact of bank size on future bank performance.

3.8 Summary and conclusion

This chapter mainly examines the impact of AMB on future bank performance in the U.S. commercial banking industry, where AMB is the interaction of EM and BE (or MA) indicators. Using a sample of 589 U.S. commercial banks from 1998 to 2017, we find that AMB could be an important indicator in the banking studies.

We find a positive association between AMB and future bank performance. Our evidence suggests that commercial banks that artificially boost earnings for short-term profits suffer from poor future performance, especially when they are not technically efficient or when the ability of their managers is low. In contrast, banks that artificially smooth current-period earnings to retain profits are found to perform better subsequently, especially when they are also technically efficient or when the banks have able managers. We further highlight the importance of AMB in commercial banking studies by revealing that AMB can potentially dominate the size impacts on future bank performance. We find that the size effect differs for banks with superior and poor AMB.

Our results suggest bank managers to be more cautious when making business decisions, because strategies that only focus on short-term profits are usually under the costs of long-term benefits. The results also suggest managers considering their ability and the efficiency of their banks while making the EM decisions, since infrastructure and other conditions could affect bank managers' decisions, which would lead to banks' diverse prospects. Our findings further draw attention of stakeholders, investors, regulators and policy makers onto bank fundamentals that are associated with fraud accounting statements, which could potentially assist to identify distressed and undervalued banks.

Unfortunately, this study only focuses on commercial banks in the United States, thus the association between AMB and future bank performance that we found in this chapter could be sample-specific. This means that the association could be driven by U.S. regulations and banking environment, which may make our findings not applicable to other regions and countries. For instance, the minimum tier 1 capital ratio in the U.S. is 6%, whereas in the U.K. the ratio is set at 4.5%. This may affect the association between AMB and bank performance by impacting banks' earnings management incentives, bank efficiency and asset quality, etc. Therefore, further work could consider expanding the sample size and investigating whether the association between AMB and future bank performance varies across countries with various degrees of institutional transparency.

Chapter 4 The Effectiveness of TARP Funds: New Evidence from Bank Efficiency and Earnings Management Perspectives

4.1 Introduction

During the global financial crisis period, starting from 2007, the stability of the banking industry in the United States (U.S.) was significantly affected. Therefore, the U.S. Treasury office initiated the Trouble Assets Relief Program (TARP) [8] in October 2008. The programme comprised a series of government interventions to increase the availability of credit, bolster the soundness and stability of the financial system, as well as spurring the economic growth (Berger and Roman, 2015; Jang, 2017; Semaan and Drake, 2016; Calabrese, Degl'Innocenti & Osmetti, 2017; Contessi, De Pace and Guidolin, 2020). This research mainly focuses on the Capital Purchase Program (CPP) and the Community Development Capital Initiative (CDCI) because CPP and CDCI are the primary components of the TARP programme that provided funds and liquidity to the U.S. banking industry. Focusing on the U.S. banking industry, this study aims to investigate the impact of TARP capital injections on bank attributes.

Previous studies have documented the impact of TARP injections on banks' market value, market power (Berger and Roman, 2015), risk taking (Wang, 2013; Black and Hazelwood, 2013; Jang, 2017), lending behaviour, (Li, 2013) and CEO benefits (Nwaeze, Xu and Yin, 2018). Prior literature has also documented that TARP-recipient banks were motivated to hide some earnings or manipulate downwards with the objective of obtaining further favourable treatment by the program administrators (Fan, Huang, Jiang and Liu, 2020). Regarding the effect of TARP on bank efficiency, Harris, Huerta and Ngo (2013) for instance, concluded that TARP recipients experienced deterioration in operating efficiency, whereas no evidence shows that the same experience occurred among non-TARP recipients.

Bank efficiency (BE) can be driven by firm-specific drivers and manager-specific drivers (Demerjian, Lev and McVay 2012). In other words, BE comprises firm-specific bank efficiency (FBE) and manager-specific bank efficiency (MBE), where FBE denotes banks' pure efficiency and MBE is the efficiency component that is dominated by bank managers. The decomposition of bank efficiency could help understand how the actual force of a programme or law acts on bank performance. However, there is no study that documents which factor-driven efficiency had been affected by TARP capital injections. Our study is expected to fill this research gap.

[8] For more information of the TARP, please refer to the Federal Reserve's website at https://www.federalreserve.gov/supervisionreg/tarpinfo.htm.

Additionally, attention has rarely been paid to the impact of capital injections on banks' earnings management (EM) activities. Earnings management is an artificial way for banks to achieve their earnings targets that are set based on their past performance, peer performance, business goals, and manager preferences. Studying banks' EM practices around TARP periods would help explain whether the TARP programme had affected banks' performance, integrity, and transparency, which further explores whether the capital injections had benefited the recipients and the banking industry in the long term. Therefore, this study also investigates the impact of TARP on banks' EM activities.

The U.S. government bailed out distressed banks via TARP during the Global financial crisis period using taxpayers' money. Consequently, taxpayers have the right to know the detailed status of banks prior to the financial crisis, and how well their money had been used to improve the performance of those distressed banks. Furthermore, the more details that are explored from previous experience of rescuing distressed banks, the better the scheme could be potentially planned when confronting similar situations in the future. These reasons also make our study consequential.

We motivate the chapter by first exploring the association between TARP programme and EM of commercial banks. Banks engage in income-increasing (aggressive) earnings management to artificially increase earnings and conduct income-decreasing (conservative) earnings management to artificially smooth earnings. Banks may have engaged in more aggressive EM activities post-TARP to show off their performance and attract more customers to achieve their ambitions of paying off the TARP funds and escape from the TARP supervision scrutiny. Banks could also have less intention and chances to manipulate earnings upwards due to TARP's additional monitoring and scrutiny. Moreover, in the long term, bank managers' ambition and additional monitoring from TARP are likely to be weakened. Therefore, we hypothesize that TARP had no significant impact on banks' decisions of EM practices in the long term.

We also hypothesize that the pure efficiency (FBE) of TARP recipients was not affected by TARP infusions because the foundations of banks such as bank age and size were unlikely to be affected by the capital injections. As for manager-specific bank efficiency (MBE), TARP may hurt MBE since TARP bank managers may have put less effort into improving bank efficiency due to the compensation thresholds that were required by TARP. On the other hand, bank managers could also work hard to boost bank efficiency and business returns to repay TARP funds and escape from the TARP restrictions. However, these two drivers are likely to be weaker in the long term, especially after banks fully repaid the funds.

Therefore, we further hypothesize that TARP had no impact on banks' long-term manager-driven bank efficiency (MBE).

We test the hypotheses mentioned above using a sample of 82 commercial banks, 199 bank holding companies, and 317 matched control banks from 2005 to 2013 in the United States. Our evidence from the difference in difference tests and baseline regressions support our hypotheses that TARP did not affect banks' EM, FBE, and MBE in the long term, suggesting that TARP rescued banks from distress but did not fundamentally change the performance of its recipients. We also find that EM, FBE and MBE had uncertain changes in the post-TARP period for all the estimated banks and that TARP banks did not perform differently from non-TARP banks among the whole sample period.

These findings are further supported by a series of robustness checks, controlling for potential dynamic endogeneity, selection bias, TARP repayment effects, global financial crisis effects, first-order autoregressive issues, and potential modelling issues caused by non-normally distributed error terms. Our empirical analysis results also suggest that commercial banks and bank holding companies who received larger amounts of TARP funds had better firm-specific bank efficiency than other TARP recipients in the following three years after the capital infusion.

This study contributes to the literature on earnings management (EM) and bank efficiency (BE) by explaining their associations with bailouts after the global financial crisis. This chapter is among the first to study the impact of government interventions on bank's engagement of earnings manipulation practices, pure efficiency, and manager-driven efficiency. Our evidence indicates that, compared to non-recipients, TARP did not affect recipients' fundamental operation, business decisions, and efficiency in the long term. In other words, TARP assisted banks during the global financial crisis period and may have only affected recipients in the short term. Banks return to their normal business schedule after surviving from the economic recession, which implies that we do not observe a long-term moral hazard phenomenon following the TARP infusions.

Additionally, in prior studies, attention has been paid to improve the bank efficiency estimation (see for example, Behr, 2010; Wanke, Barros and Emrouznejad, 2016; Asmild and Zhu, 2016; Quaranta, Raffoni and Visani, 2018; Tsionas and Mamatzakis, 2019) but the factor-driven bank efficiency has not been well introduced and addressed. Furthermore, management can be a portion of bank technology (Delis, Iosifidi and Tsionas, 2020) and manager’s ability is hard to be measured. Therefore, although previous studies have decomposed the bank efficiency, they frequently use the MBE part only to evaluate managers’ ability and leave out the pure bank efficiency part in the estimation (see for example, Demerjian, Lev and McVay, 2012; Andreou, Philip and Robejsek, 2016; Lee, Wang, Chiu and Tien, 2018). As far as we know, this chapter is among the first to simultaneously study banks' firm-characteristic driven efficiency (FBE) and manager-ability driven efficiency (MBE). Our study investigates the impact of TARP on those two bank efficiencies and finds that the amount of the TARP infusions did not affect managers' ability to improve bank efficiency in the long term, whereas the amount of the TARP funds positively influenced the long-term pure bank efficiency of TARP recipients. We view our finding as an evidence that although the intervention may limit managers' behaviour in the short term, government interventions can hardly affect bank managers' operating ability in the long term.

The rest of the chapter is organised as follows. Section 4.2 discusses the background of TARP and a literature review of TARP effect. Section 4.3 documents our main hypotheses. Section 4.4 presents the data and main variables generation. Section 4.5 performs the empirical analysis design. Section 4.6 presents our empirical results and discussions. Section 4.7 summarizes and concludes the chapter.

4.2 Background and literature review

4.2.1 Background of TARP

The global financial crisis (2007-2009) is a great recession caused by subprime mortgage lending. The crisis led to an unhealthy credit market and a turbulent U.S. financial system (Harris, Huerta and Ngo 2013). As a result, plenty of financial and non-financial firms bankrupted, including Lehman Brothers[9]. In response to the crisis, Troubled Asset Relief Programme (TARP) was established based on the Emergency Economic Stabilization Act of 2008[10], by the U.S. Treasury office.

The U.S. Department of Treasury initially authorized up to $700 billion for government purchases of troubled assets from financial institutions to rescue credit and improve the financial system's soundness and stability. Later on, the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank Act) reduced this authority from $700 billion to $475 billion. Within the $475 billion TARP funds, around $250 billion was committed to

---

[9] Lehman Brothers filed for Chapter 11 bankruptcy protection on September 15th, 2008.

[10] Emergency Economic Stabilization Act of 2008 was written into the law on October 3rd, 2008.

stabilize the banking industry; approximately $27 billion was committed to assisting with credit markets; about $82 billion was assigned to stabilize the U.S. auto industry, and around $70 billion was committed to rescuing distressed families from foreclosure.

There were five sub-programmes to stabilize the banking industry under TARP. The primary initiative is the Capital Purchase Programme (CPP) (Song and Uzmanoglu, 2016; Semaan and Drake, 2016; Calabrese, Degl'Innocenti & Osmetti, 2017), which allows financial institutions to sell their preferred stocks and equity warrants to the U.S. Treasury office. Financial institutions joined this programme to reduce their distress pressure from non-performing loans, especially mortgage-backed securities (MBS) due to their high default rates. CPP was established in 2008 and had provided capitals to around 707 financial institutions in 48 states. The final investment under CPP programme was made in December 2009. The second one is the Targeted Investment Programme (TIP), which was launched in December 2008. This programme added flexibility to the TARP programme by providing additional funds to distressed financial institutions to prevent broader disruption of the financial markets.

The third programme is the Asset Guarantee Programme (AGP), which was launched in January 2009. This programme had helped Bank of America and Citigroup by agreeing to absorb a portion of losses on certain assets. The fourth one is the Supervisory Capital Assessment Programme (SCAP), established in early 2009 to ensure adequate capital buffers in the U.S. major banking institutions, to undertake defaults and losses in a further economic recession. The last programme is the Community Development Capital Initiative (CDCI), established in February 2010, to assist viable certified Community Development Financial Institutions (CDFIs) and the communities they serve. CDFIs provided funds to communities that struggle to obtain credit from traditional banks, and the programme stopped providing funds in September 2010.

Although TARP, the most massive government bailout in U.S. history, may have rescued plenty of banks and companies from bankruptcy, it is still frequently considered a controversial programme. It is frequently criticized due to its way of rescuing distressed banks. For instance, Hoshi and Kashyap (2010) document that troubled banks can hardly be benefited from government capital injections because they are more likely to use the new capital to purchase riskier assets to grow profits rather than spurring the liquidity of existing loans, due to the moral hazard theory. Therefore, this chapter studies whether the moral hazard phenomenon exists in the long term by exploring the impact of TARP on banks' long-term earnings management behaviour, pure bank efficiency, and manager-driven bank efficiency.

4.2.2 Literature review

There is a growing amount of literature studying the significance of TARP from various perspectives. In general, TARP has been documented to reduce credit risks in the U.S. banking industry by reducing non-performing loans and real estate non-performing loans (Jiang, Kanas & Molyneux, 2018). TARP has also been found to help reduce economic shock transmission by providing TARP banks, that were exposed in the distressed areas, capitals to disperse their investment into small business originations in relatively non-distress areas (Jang, 2017).

TARP's impact on recipients' loan supply has been studied as well but has remained controversial. Li (2013) studies the impact of TARP funds distribution on bank loan supply and the determinants of the distribution. The author documents that TARP capital injections positively affected banks' credit supply. The author also finds that, on average, a third of the TARP capital was released for generating new loans whereas the rest were used for strengthening balance sheets. In contrast, Montgomery and Takahashi (2014) find that TARP did not stimulate banks' lending. Therefore, TARP failed to help banks with asset growth.

A few studies have also focused on the risk level of TARP recipients around TARP capital infusions. Black and Hazelwood (2013) compare the risks of loan originations of different-sized TARP banks and non-TARP banks following the TARP. They document that large TARP banks were more risk-taking whilst small TARP banks were less risk-taking than large non-TARP banks and small non-TARP banks, respectively, following TARP infusions. Farruggio, Michalak and Uhde (2013) investigate the systematic risk of banks around the first TARP announcement date, announcement revision date, TARP injection date and repayment date. They find that banks' systemic risks increased around the TARP announcement date and the TARP infusion date, but not the repayment date.

Wang (2013) also documents that TARP had an adverse impact on bank runs, making TARP banks risky. Bank runs occur when bank depositors attempt to withdraw more money than the bank can provide. The author finds that the implementation of TARP reduced non-TARP banks' probability of bank runs but the probability increased significantly when the non-TARP banks were announced to receive TARP capital injections. Banks depositors may have treated TARP capital infusions as a negative sign to the recipients because the infusion implies that the banks' asset quality is poor.

More recently, Semaan and Drake (2016) investigate the long-term systematic and idiosyncratic risks of TARP participants and find that TARP participants, particularly CPP recipients, had higher idiosyncratic risks in common stocks than non-participants for over four years after CPP. However, even though TARP banks are found to be potentially more risk-taking, they are also captured to be more competitive post-TARP, as documented by Berger and Roman (2015). They find that TARP helped banks expand their market shares as well as market power. The authors further find that TARP banks that repaid early received even more competitive advantages than other TARP recipients.

TARP has also been found to affect banks' CEO behaviour. Due to the TARP restrictions on CEOs' total annual compensation, CEOs were expected to resign from TARP banks after capital infusions proactively. Nwaeze, Xu and Yin (2018) find that following TARP, bank performance increased after CEOs exiting the bank, especially in the year following the CEO resignation. They also find that banks that experienced CEO resignation performed better following the TARP than banks that retained their CEOs. Therefore, the authors suggest that TARP improved the performance of recipient banks.

Harris, Huerta and Ngo (2013) also document that bank performance could be affected by TARP capital injections. They investigate the association between TARP and commercial banks' operational efficiency in the six quarters following TARP capital injections. Their empirical results from difference in difference tests, Tobit regressions and General Method of Moment (GMM) regressions suggest that the operation efficiency of TARP banks decreased significantly more than non-TARP banks following the TARP funds injections, due to the moral hazard phenomenon. This means that government interventions via TARP reduced recipients' engaging in best practices to improve the structure of their assets because the government undertook their business risks by providing further funds to help them survive. They also document that the amount of TARP capital infusions was negatively correlated with commercial banks' operational efficiency. Their research is highly relevant with our study. Our research focuses on the impact of TARP on bank efficiency over a longer period and further divides banks' operational efficiency into firm-specific bank efficiency and manager-specific bank efficiency to investigate which part of the bank efficiency was mainly affected by the more extended funds.

4.3 Hypotheses

Banks engage in income-increasing earnings management to artificially increase earnings and conduct income-decreasing earnings management to artificially smooth earnings (Kanagaretnam, Lobo and Mathieu, 2004). Banks manipulate earnings to achieve or beat benchmarks (Dong and Zhang 2018), whilst the earnings benchmarks can be affected by banks' previous-period performance and the performance of their peers. Banks' previous returns and their peer returns are expected to be consistent regardless of TARP banks' capital infusions. Under this circumstance, banks' EM behaviour is expected to be consistent after TARP capital injections.

Furthermore, banks conduct less EM practices when their manipulation incentives and opportunities are limited, and information asymmetry is relatively low (Cornett, McNutt and Tehran 2009; Jin, Kanagaretnam, Lobo and Mathieu, 2013; Li, Ma and Song, 2018) [11]. TARP recipients are expected to have lower information asymmetry than non-TARP banks due to the TARP programme's additional supervision and scrutiny, subject to the section 111 of the Emergency Economic Stabilization Act of 2008. For instance, TARP recipients were required to disclose any perquisites annually during the TARP period to the Treasury. These would decrease banks' engagement in EM activities by demotivating managers' manipulation incentives, which would decrease banks' EM practices.

In contrast, TARP banks may have more incentives to manipulate earnings because they may have relatively high risk-taking preferences to attract more customers and achieve higher profits to repay the TARP funds. Risks are positively associated with earnings volatility, which may stimulate bank managers' EM incentives, causing more aggressive EM activities. Furthermore, banks may have engaged in more aggressive EM activities post-TARP to show off their performance and attract more customers to achieve their ambitions of paying off the TARP funds and escape from the TARP supervision and scrutiny. The above reasons may lead to an irrelevant association between TARP and banks' EM practices. Furthermore, in the long term, bank managers' ambition and additional monitoring from TARP are like to be weakened. Accordingly, our first hypothesis is:

Hypothesis 1. TARP capital injections have no significant impact on recipients' earnings management behaviour in the long term.

TARP recipients were under the pressure of repaying the capital infusions provided by U.S. Treasury office. Therefore, banks may have worked on increasing their lending activities with less consideration of loan quality (Harris, Huerta and Ngo 2013), leading to a bad firm-

---

[11] When banks' renenue meet their targets, they have less incentives to manipulate earnings, therefore, those banks conduct less aggressive EM activities. Banks also engage in less EM practices when they are under strict supervision from the Federal Reserve Board, which provides them less opportunities to manipulate earnings. Additionally, when the information asymmetry is low, banks' aggressive EM practices are more likely to be captured by the public, therefore, reduces their EM intentives.

specific bank efficiency (FBE). Additionally, increased scrutiny and monitoring that were conducted by the TARP programme could restrict bank activities, whilst bank activity restrictions were negatively associated with bank efficiency (Barth, Lin, Ma, Seade and Song 2013). This would suggest a negative impact between TARP and FBE. Moreover, TARP funds provided distressed banks opportunities to keep operating inefficiently instead of considering restructuring their business strategies. Therefore, the profitability of those banks may remain at a low level. Less profitable banks are less likely to be technically efficient (Miller and Noulas 1996) because less efficient banks are less likely to attract customers in a competitive industry. Therefore, TARP capital infusions may be negatively associated with banks' pure bank efficiency in the short term whereas in the long term, the above mentioned incentives are likely to be weaker, especially after TARP repayments.

While the above evidence suggests that TARP could lower efficiency, we could also envisage reasons that would cause TARP-recipients to become more efficient after capital injections. TARP supervised banks and relatively restricted their aggressive activities, whereas proper supervision could help banks overcome market failures by reducing imperfect information (Miller and Noulas 1996). Less information asymmetry would attract reliable depositors, lenders and investors, and consequently increase banks' capital quality and operational performance. Furthermore, TARP capital infusions are expected to assist in strengthening the financial system and rebuilding public confidence in the banking industry. Therefore, TARP recipients may be favoured by the public due to government support and guarantees that they had been provided. Also, banks with a relatively high reputation would reduce their capital costs because depositors would prefer capital safety instead of high returns during economic recessions. Consequently, TARP banks could have more FBE than non-TARP banks in the short term. However, in the long term, the above mentioned incentives are also likely to be weaker, especially after the TARP repayments and the economic recessions.

Overall, our second testable hypothesis is as follows:

Hypothesis 2. TARP capital injections have no significant impact on recipients' firm-specific efficiency in the long term.

TARP recipients suffer from increased scrutiny and monitoring by the TARP programme compared with non-TARP recipients. Therefore, managers from TARP banks would undertake more stress and receive less flexibility when making business strategies. Managers' stress is negatively associated with firms' performance (Mohr and Puck, 2007), and the efficiency is a reflection of firm performance. Therefore, manager-specific bank efficiency (MBE) would be an adverse reflection of manager's stress, which refers to a negative association between TARP fund injections and MBE. Moreover, the TARP programme required TARP recipients to have a salary threshold of up to $500,000[12]. Managers could be demotivated due to the restriction that the TARP programme imposed on their compensation. Consequently, demotivated managers could negatively affect their manager-specific bank efficiency in the short term; however, the above-mentioned incentives are likely to be weaker in the long run, especially after TARP repayments.

If managers positively respond to the payment threshold, they would work harder to repay the TARP funds to get rid of the payment restriction. Also, if the managers' initial payments were above the payment threshold, then they would have to work harder for additional bonuses to achieve their initial payment levels. Consequently, TARP capital injections may have positive effect on banks' manager-specific efficiency. Furthermore, TARP banks have been found to take more risks than non-TARP recipients following the capital injections, due to the moral hazard phenomenon (Wang, 2013; Semaan and Drake 2016). High risks are typically associated with high returns. Therefore, this phenomenon implies that TARP bank managers were keen to achieve more profits and repay TARP funds. The positive reactions from managers were likely to contribute to a high bank efficiency post-TARP in the short term but in the long term, the above mentioned incentives are likely to be weaker, especially after TARP repayments.

According to the reasons mentioned above, the third hypothesis is proposed as follows:

Hypothesis 3. TARP capital injections have no significant impact on recipients' manager-specific efficiency in the long run.

---

[12] More information is available the U.S. Department of the Treasury website at https://www.treasury.gov/press-center/press-releases/Pages/tg329.aspx.

4.4 Data and variables

4.4.1 Data

We obtain annual financial data of 982 commercial banks and 1114 bank holding companies from the Fitchconnect database, and obtain the list of banks that had received TARP capital infusions from the U.S. Department of Treasury website across the period 2005 to 2013. Firms with missing data, particularly total assets data, are removed from the initial dataset for analysis purposes, leaving us 597 commercial banks and 947 bank holding companies. We then match our initial dataset with the TARP recipient dataset and generate a TARP recipient sample consisting of 82 commercial banks and 199 bank holding companies. Table 26 panel A lists the number of TARP capital injections captured in this chapter each year.

The average size of assets for TARP commercial banks in our sample is around 117,000 million dollars for the entire estimated period, while for all of the non-TARP commercial banks is only about 24,000 million dollars. This implies that TARP favoured large commercial banks instead of their medium and small competitors. The average assets of TARP bank holding companies are approximately 4,400 million dollars, and that of all the non-TARP bank holding companies are around 7,230 million dollars as shown in panel C. This finding indicates that TARP favoured slightly smaller bank holding companies, which may because smaller bank holding companies were more likely to need capital infusions from the government to resist distress.

We then match control groups for TARP commercial banks and TARP bank holding companies, respectively, based on banks' total assets in the TARP injection year. One to two banks with the closest amount of total assets with corresponding TARP recipients are selected as control banks (i.e., non-TARP banks). The final dataset is an unbalanced dataset comprising 82 commercial banks, 199 bank holding companies and 317 control banks over the period 2005 to 2013.

The matched sample summaries are shown in Table 26 panel B and panel C for commercial banks and bank holding companies, respectively. The results show that the TARP injection amount is, in general, 2.3% of banks' total assets for both commercial banks and bank holding companies. We match control banks with test banks based on banks' total assets at the TARP capital infusion year. Therefore, the average, minimum, and maximum total assets of the test banks and the control banks could still vary to an extent.

Table 26 Sample summaries

This table reports descriptive summary statistics on TARP funding. TARP banks are matched based on banks' total assets in the TARP injection year. 281 banks and bank holding companies received TARP funds from 2008 to 2010. The non-TARP banks in this table are un-matched banks. We display un-matched instead of matched non-TARP recipients in this table, because our main criteria to match the control group is total assets. Using matched banks would make the comparison meaningless in this table.

Panel A TARP funds injections by year								
	Commercial banks				Bank holding companies			
	2008	2009	2010	total	2008	2009	2010	total
No. of banks	54	26	2	82	80	114	5	199
TARP Injection ($Million)	2429.898	65.931	11.368	1621.359	191.868	28.158	19.091	93.743

Panel B Commercial banks										
	TARP banks					Non-TARP banks				
	Mean	Median	Min	Max	Std. Dev.	Mean	Median	Min	Max	Std. Dev.
Total Assets ($Million)	117000	8840	75.7	2270000	376000	74500	7670	2.7	2260000	275000
TARP Injection ($Million)	1621.4	122.5	0.7	25000	4996.5	\	\	\	\	\
TARP Injection/ Total Assets	2.319%	2.196%	0.002%	11.869%	1.582%	\	\	\	\	\

Panel C Bank holding companies										
	TARP banks					Non-TARP banks				
	Mean	Median	Min	Max	Std. Dev.	Mean	Median	Min	Max	Std. Dev.
Total Assets ($Million)	4400	1150	127	340000	22900	6780	1020	45.5	668000	43100
TARP Injection ($Million)	93.7	22.0	1.7	6599.0	508.4	\	\	\	\	\
TARP Injection/ Total Assets	2.287%	2.139%	0.035%	20.745%	2.211%	\	\	\	\	\

4.4.2 Main Variables

This section comprises two parts. The first part introduces measures of earnings management and the second part presents the measure of firm-specific bank efficiency and manager-specific bank efficiency.

Earnings management (EM)

EM is measured based on discretionary loan loss provisions (DLLPs) and discretionary loan loss reserves (DLLRs), following Adams, Carow and Perry (2009). DLLPs and DLLRs are residuals derived from Loan loss provisions (LLPs) and loan loss reserves (LLRs) models as follows, respectively.

$$\mathrm{LLP_{it}} = \alpha + \beta_1 \mathrm{Ln(assets)_{it}} + \beta_2 \Delta\mathrm{NPA_{it}} + \beta_3 \frac{\mathrm{Chargeoffs_{it}}}{\mathrm{Aloans_{it}}} + \beta_4 \frac{\mathrm{LLP_{i,t-1}}}{\mathrm{Aloans_{it}}} + \text{year dummies} + \varepsilon_{\mathrm{it}} \quad (30)$$

$$\mathrm{LLR}_{\mathrm{it}} = \alpha + \beta_1 \mathrm{Ln(assets)}_{\mathrm{it}} + \beta_2 \Delta\mathrm{NPA}_{\mathrm{it}} + \beta_3 \frac{\mathrm{Chargeoffs}_{\mathrm{it}}}{\mathrm{Aloans}_{\mathrm{it}}} + \beta_4 \frac{\mathrm{LLR}_{\mathrm{i,t-1}}}{\mathrm{Aloans}_{\mathrm{it}}} + \text{year dummies} + \varepsilon_{\mathrm{it}} \tag{31}$$

Where $\mathrm{LLP}_{\mathrm{it}}$ is the Loan loss provisions ratio, defined as the ratio of loan loss provisions to average loans of bank i at year t; $\mathrm{LLP}_{\mathrm{i,t-1}}$ denotes loan loss provisions ratio of bank i at year $\mathrm{t}-1$; $\mathrm{Ln(assets)}_{\mathrm{it}}$ is the natural logarithm of total assets of bank i at year t; $\Delta\mathrm{NPA}_{\mathrm{it}}$ represents difference changes of non-performing loans to average loans ratio of bank i at year t; $\mathrm{Chargeoffs}_{\mathrm{it}}$ is the net charge-offs of bank i at year t; $\mathrm{Aloans}_{\mathrm{it}}$ denotes average loans of bank i at year t; $\mathrm{LLR}_{\mathrm{it}}$ and $\mathrm{LLR}_{\mathrm{i,t-1}}$ represent loan loss reserves ratio, which is defined as the ratio of loan loss reserves to average loans of bank i in year t and year $\mathrm{t}-1$, respectively.

We take negative values of DLLP and DLLR as our final measurement of EM, naming EM1 (-DLLPs) and EM2 (-DLLRs), respectively, to better fit the economic meaning of earnings management. A large and positive value of EM1 (or EM2) indicates banks' income-increasing earnings manipulation, while a small and negative value of EM1 (or EM2) indicates banks' income-decreasing earnings manipulation.[13] Banks can also use realised security gains and losses to manipulate earnings. We do not capture this type of EM because it is found to be less effective at capturing banks' EM practices than using DLLPs (Cohen, Cornett and Marcus, 2014).

Bank efficiency (BE)

Bank efficiency (BE) is measured by a non-parametric method using Data Envelopment Analysis (DEA). We use a DEA model instead of parametric analysis methods to avoid errors from misspecifications in designing frontier functions. A multi-stage input-oriented DEA model suggested by Coelli (1998) is used in this chapter, and the DEA model is estimated by year to eliminate year effects. We use three inputs and three outputs following Harris, Huerta and Ngo (2013), to estimate banks' technical efficiency. Non-interest expenses to assets ratio (NIETA), interest expenses to assets ratio (IETA) and deposits to assets ratio (DTA) are adopted as inputs, while loans to assets ratio (LTA), non-interest incomes to assets ratio (NIITA) and interest incomes to assets ratio (IITA) are applied as outputs.

[13] Please refer to Appendix CI for the mean value of estimated banks' EM1 and EM2 from 2003 to 2017.

According to Demerjian, Lev and McVay (2012), firm efficiency can be driven by firm-specific efficiency drivers and manager-specific efficiency drivers. Firm-specific efficiency drivers denote firms' primary attributes that could affect their technical efficiency, whilst manager-specific drivers are firm managers' characteristics and their abilities to impact firms' efficiency. Following Demerjian, Lev and McVay (2012) and Andreou, Philip and Robejsek (2016), we parse out BE into firm-specific efficiency (FBE) and manager-specific efficiency (MBE), in order to better study the impact of TARP funds on banks' resource utilization. We model bank efficiency based on firm-specific efficiency drivers per Andreou, Philip and Robejsek (2016) using the following equation.

$$BE_{it} = \alpha + \beta_1 Ln(assets)_{it} + \beta_2 Ln(employee)_{it} + \beta_3 Ln(age)_{it} + \beta_4 Leverage_{it} + \beta_5 FCF_{it} + \varepsilon_{it} \quad (32)$$

Where $Ln(assets)_{it}$ denotes the nature logarithm of total assets of bank i at year t; $Ln(employee)_{it}$ represents the nature logarithm of employee number of bank i at year t; $Ln(age)_{it}$ is the age of bank i at year t; $Leverage_{it}$ denotes the leverage ratio of bank i at year t, which is defined as the ratio of total assets to total equity; and FCF_{it} is the asset liquidity indicator of bank i at year t, taking a value of one for positive cash flow years, zero otherwise. The residual from equation (32) is defined as MBE. MBE is the amount of bank efficiency that is driven by managers. Additionally, we subtract MBE from BE and define the rest as FBE. FBE is banks' pure firm-efficiency without the impacts of bank managers. Studying FBE and MBE individually can help investors better understand banks' efficiency structure.[14]

The mean values of MBE and FBE are close to zero, and MBE and FBE that are extracted from equation (32) can be both positive and negative, whereas it is difficult to explain the economic meanings for negative efficiency scores. Therefore, we use a transformation approach developed in section 3.5.2 to restrict MBE and FBE between 0 and 1. The transformation is conducted on a year basis, and the equation is as follows.

$$\mathrm{FA}_{\mathrm{i,t}} = \frac{1}{1 + \mathrm{e}^{\left(-\frac{5.8}{\max_t - \min_t} * \mathrm{A}_{\mathrm{i,t}}\right)}} \quad (33)$$

Where A is the variable that needs to be transferred; FA represents the transformed A; max and min denote the maximum and minimum value of A at time t, respectively. We use this equation to track the value 0, which equals to 0.5 after the transformation, in the original

[14] Please refer to Appendix CI for the mean value of estimated banks' FBE and MBE between 2003 and 2017.

data set. Please note that 0 is not necessarily a mean value in each year. After the transformation, a below 0.5 MBE (FBE) indicates that bank efficiency suffers from manager-specific (firm-specific) efficiency drivers, while an above 0.5 MBE (FBE) indicates that bank efficiency benefits from manager-specific (firm-specific) efficiency drivers.

4.5 Empirical analysis design

The primary purpose of this research is to study the impact of TARP fund infusions on banks' earnings management activities (EM), firm-specific bank efficiency (FBE), and manager-specific bank efficiency (MBE). We first set the pre-TARP period as three years prior to the capital injection year and set the post-TARP period as three years after the capital infusion year. We then compare EM, FBE and MBE between pre- and post-TARP periods for TARP recipients and non-TARP banks respectively. We also compare EM, FBE and MBE between TARP recipients and non-TARP banks for pre- and post-TARP periods, respectively. Most importantly, we conduct difference in difference tests using the differences between TARP recipients and non-TARP banks and the differences between pre- and post-TARP periods, to investigate how the TARP capital injections affect banks' EM, FBE and MBE. We apply all of our analysis to commercial banks and bank holding companies, respectively.

Next, we control the impact of other bank attributes on EM, FBE and MBE by conducting baseline regressions. The dependent variables are earnings management, firm-specific bank efficiency and manager-specific bank efficiency. We investigate whether EM, FBE and MBE for TARP and non-TARP banks, respectively, change significantly between pre- and post-TARP periods, by running a fixed-effect Ordinary Least Squared (OLS) regression provided as follows.

$$\begin{aligned}\mathrm{BA_{i,t}} = \alpha + \beta_1 \mathrm{POST\_TARP\ PERIOD_{it}} + \beta_2 \mathrm{Ln(assets)_{it}} \\ + \beta_3 \mathrm{Non\_performing\ loans\ to\ gross\ loans_{it}} \\ + \beta_4 \mathrm{returns\ on\ assets_{it}} + \beta_5 \mathrm{liquid\ assets\ to\ total\ assets_{it}} \\ + \beta_6 \mathrm{net\ charge\ offs\ to\ total\ loans_{it}} + \beta_9 \mathrm{BA_{i,t-1}} + \varepsilon_{it}\end{aligned} \tag{34}$$

Where $BA_{i,t}$ denotes the bank attributes EM, FBE and MBE, respectively, for bank i in the year t; and $BA_{i,t-1}$ is the lagged value of the corresponding dependent variable, capturing dynamic impacts of the dependent variable. $POST\_TARP\ PERIOD_{it}$ is a dummy that takes a value of one for the three years after the year that the bank received TARP funds or for the three years after the year that the control bank's corresponding TARP recipient received

TARP funds. The dummy takes zero for the three years before the year that the bank received TARP funds or for the three years before the year that the control bank's corresponding TARP recipient received TARP funds.

We then compare whether the TARP and non-TARP banks have significantly different EM, FBE and MBE at the pre- and post-TARP periods, respectively, by conducting a random-effect Generalized Least Squared (GLS) regression formulated as follows.

$$\begin{aligned} \mathrm{BA}_{i,t} = {} & \alpha + \beta_1 \mathrm{TARP\ BANK}_i + \beta_2 \mathrm{Ln(assets)}_{it} \\ & + \beta_3 \mathrm{Non\_performing\ loans\ to\ gross\ loans}_{it} \\ & + \beta_4 \mathrm{returns\ on\ assets}_{it} + \beta_5 \mathrm{liquid\ assets\ to\ total\ assets}_{it} \\ & + \beta_6 \mathrm{net\ charge\ offs\ to\ total\ loans}_{it} + \beta_9 \mathrm{BA}_{i,t-1} + \varepsilon_{it} \end{aligned} \tag{35}$$

Where $TARP\ bank_i$ takes a value of one if bank i is a TARP recipient, taking a value of zero if the bank i does not receive any TARP funds (i.e., banks in the control group). The firm effect is not fixed in this model because our main variables of interest $TARP\ BANK_i$ is highly correlated with firm-fixed effect indicators.

Finally, we study the impact of the TARP infusions on banks' EM, FEB and MBE using a random-effect GLS model presented as follows.

$$\begin{aligned} \mathrm{BA}_{i,t} = {} & \alpha + \beta_1 \mathrm{POST\_TARP\ PERIOD}_{it} + \beta_2 \mathrm{TARP\ BANK}_i + \beta_3 \mathrm{TARP\ BANK}_i \\ & * \mathrm{POST\_TARP\ PERIOD}_{it} + \beta_4 \mathrm{Ln(assets)}_{it} \\ & + \beta_5 \mathrm{Non\_performing\ loans\ to\ gross\ loans}_{it} \\ & + \beta_6 \mathrm{Returns\ on\ assets}_{it} + \beta_7 \mathrm{Liquid\ assets\ to\ total\ assets}_{it} \\ & + \beta_8 \mathrm{Net\ charge\ offs\ to\ total\ loans}_{it} + \beta_9 \mathrm{BA}_{i,t-1} + \varepsilon_{it} \end{aligned} \tag{36}$$

Where we have three variables of interest and two of them ($TARP\ BANK_i$ and $POST\_TARP\ PERIOD_{it}$) have been defined in the previous models. Our primary variable of interest is $TARP\ BANK_i * POST\_TARP\ PERIOD_{it}$, an interaction of $TARP\ BANK_i$ and $POST\_TARP\ PERIOD_{it}$ dummies. Similar as equation (35), the firm effect is not fixed in this model because one of our main variables of interest $TARP\ bank_i$ is highly correlated with firm-fixed effect indicators.

We adopt OLS and GLS approaches as baseline models in this chapter because our dependent variables, EM, FBE and MBE, are bounded not censored. Table 27 presents the correlation coefficients of variables involved in our analysis.

4.6 Empirical results and discussion

This section reports and discusses the empirical analysis results. The analysis is conducted for commercial banks and bank holding companies, respectively, unless stating otherwise.

4.6.1 Univariate analysis

Table 28 reports the results of the difference in mean tests on earnings management (EM), firm-specific bank efficiency (FBE), and manager-specific bank efficiency (MBE) between TARP and non-TARP banks by year. Panel A, Panel B, Panel C and Panel D report results for EM1, EM2, FBE and MBE, respectively. The T-test results for commercial banks are all insignificant, suggesting no significant EM, FBE and MBE differences between TARP and non-TARP banks for every estimated year. This means that TARP banks' earnings manipulation activities and efficiency are not distinct from non-TARP banks during both the prior- and post-TARP periods. Previously, Harris, Huerta and Ngo (2013) find that TARP banks are generally less efficient than non-TARP banks during the six quarters following the capital injection. Our evidence, however, suggests that TARP does not show any significantly negative impacts on bank efficiency, when splitting the efficiency into firm-specific and manager-specific ones. The inconsistency may be explained by the use of distinct TARP and non-TARP matching methods.

As for bank holding companies, the difference in mean of earnings management indicator 1 (EM1) between TARP and non-TARP banks in year one is negative and significant at 5% level (-0.174). This indicates that TARP banks manipulate earnings less than non-TARP banks in the year after capital injections, which may be due to TARP's additional monitoring. However, we do not observe any significant differences in earnings management indicator 2 (EM2) between TARP and non-TARP banks in the same year (-0.001). This means that EM's difference between TARP and non-TARP banks in the year after capital injections stays unclear. Furthermore, the FBE (-0.071) and MBE (-0.056) of TARP banks are lower than non-TARP banks in the year and one year following the TARP infusions for bank holding companies. These results suggest that bank holding companies that received TARP funds underperform non-TARP firms in the short term.

Table 27 Correlation matrix

This table presents the correlation coefficients between variables included in the main empirical analysis. TARP amount is only marked for the post-TARP period.

	EM1	EM2	FBE	MBE	TARP bank	Post-TARP period	Ln(assets)	Non-performing loans to gross loans	ROA	Liquid assets to total assets	Net charge offs ratio	TARP amount	Tarp repayments
EM1	1.000												
EM2	0.448***	1.000											
FBE	0.066***	0.072***	1.000										
MBE	0.001	0.000	0.030***	1.000									
TARP bank	-0.045**	-0.023	-0.061***	-0.036*	1.000								
Post-TARP period	-0.008	-0.014	-0.022	0.011	0.001	1.000							
Ln(assets)	0.000	0.000	0.319***	0.007	0.033*	0.049***	1.000						
Non-performing loans to gross loans	-0.005	0.004	-0.245***	-0.107***	-0.030*	0.022	-0.003	1.000					
Returns to total assets	0.125***	0.013*	0.225***	0.285***	-0.048***	-0.038**	0.008	-0.106***	1.000				
Liquid assets to total assets	0.012	-0.007	0.072***	-0.064***	-0.061***	0.004	0.190***	0.064***	0.075***	1.000			
Net charge offs to total loans	-0.000	0.000	-0.074***	0.024***	0.026	0.324***	0.047***	0.010	0.067***	0.028***	1.000		
TARP amount	0.019	-0.006	0.210***	-0.071**	.	.	0.628***	-0.030	0.051*	0.795***	0.133***	1.000	
TARP repayments	0.004	0.003	0.103***	0.019	0.047***	0.003	0.168***	-0.044**	0.015	0.107***	-0.052***	0.143***	1.000

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

Table 28 Descriptive statistics of earnings management (EM), firm-specific bank efficiency (FBE) and manager-specific bank efficiency (MBE).

This table reports summary statistics on EM, FBE and MBE for commercial banks and bank holding companies, respectively. This table also reports difference in mean tests results of EM, FBE and MBE between TARP recipients and non-TARP banks in each fiscal year, for commercial banks and bank holding companies, respectively. We report summary statistics up to three years prior to the TARP injection year and three years following the injection year. Year 0 is the TARP infusion year in this table.

	Commercial banks			Bank holding companies		
Year	TARP banks (1)	Non-TARP banks (2)	Difference (1)-(2) t-stat.	TARP banks (3)	Non-TARP banks (4)	Difference (3)-(4) t-stat.
Panel A Earnings management measure 1 (EM1)						
-3	0.007	0.009	-0.002	-0.019	0.018	-0.037
-2	0.014	0.002	0.012	0.015	-0.018	0.033
-1	-0.011	0.053	-0.063	-0.057	0.023	-0.080
0	-0.062	-0.055	-0.007	-0.056	0.019	-0.076
1	-0.093	-0.009	-0.084	-0.092	0.082	-0.174**
2	-0.067	0.072	-0.139	-0.012	0.033	-0.045
3	0.064	0.027	0.037	-0.068	-0.037	-0.030
Panel B Earnings management measure 2 (EM2)						
-3	0.011	0.054	-0.043	0.015	0.009	0.006
-2	-0.020	0.021	-0.041	-0.002	0.005	-0.006
-1	-0.0002	0.053	-0.053	-0.084	0.027	0.111
0	-0.079	-0.028	-0.051	-0.031	-0.036	0.005
1	-0.035	-0.059	0.025	0.044	0.045	-0.001
2	-0.143	0.019	-0.162	-0.051	-0.027	-0.024
3	0.059	0.009	0.050	-0.027	-0.008	-0.019
Panel C Firm-specific bank efficiency (FBE)						
-3	0.531	0.509	0.022	0.508	0.512	-0.004
-2	0.521	0.513	0.008	0.515	0.517	-0.002
-1	0.521	0.522	-0.002	0.515	0.535	-0.020
0	0.510	0.513	-0.003	0.514	0.554	-0.040
1	0.448	0.477	-0.030	0.470	0.541	-0.071**
2	0.511	0.550	-0.039	0.485	0.514	-0.028
3	0.533	0.549	-0.016	0.507	0.517	-0.009
Panel D Manager-specific bank efficiency (MBE)						
-3	0.413	0.454	-0.041	0.475	0.468	0.006
-2	0.473	0.475	-0.002	0.483	0.441	0.042
-1	0.491	0.489	0.003	0.459	0.476	-0.017
0	0.514	0.499	0.015	0.426	0.483	-0.056*
1	0.437	0.482	-0.045	0.463	0.489	-0.027
2	0.468	0.454	0.014	0.476	0.487	-0.011
3	0.455	0.484	-0.029	0.446	0.481	-0.035

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

Table 29 presents the results of difference in difference tests and the mean tests of EM, FBE and MBE during the three-year pre-TARP periods and the three-year post-TARP periods. Table 29 Panel A, B, C and D report results of EM1, EM2, FBE and MBE, respectively. The results from both difference in mean tests and difference in difference tests of commercial banks in all panels are statistically insignificant, except the difference in difference test result for FBE (-0.035). Nevertheless, it is only significant at the 10% level, which may occur due to uncontrolled factors such as banks' revenue levels. These results are consistent with the findings obtained from Table 28, which is that TARP does not affect commercial banks' EM, FBE and MBE.

For bank holding companies, the differences of EM1 and EM2 between TARP and non-TARP banks during both pre- and post-TARP periods are not statistically significant in Panel A and B, apart from EM1 (-0.080) shows a 10% level of significance at the post-TARP period. These results indicate that TARP banks conduct similar EM practices as non-TARP banks regardless of government interventions. The differences of EM1 and EM2 between pre-TARP and post-TARP periods are statistically insignificant for both TARP recipients and non-TARP banks, suggesting that both TARP and non-TARP banks' EM activities are not affected by TARP capital infusions. More importantly, the difference in difference test results for both EM indicators are insignificant. This finding is consistent with our Hypothesis 1 that TARP capital injections have no significant impact on recipients' earnings management behaviour.

Table 29 Statistical test results on earnings management (EM), firm-specific bank efficiency (FBE) and manager-specific bank efficiency (MBE).

This table reports difference-in-difference test results of EM, FBE and MBE three years after the TARP capital injections compared with three years before the capital infusions between TARP and non-TARP banks, for commercial banks and bank holding companies, respectively.

	Commercial banks			Bank holding companies		
	TARP banks (1)	Non-TARP banks (2)	Difference (1)-(2) t-stat.	TARP banks (3)	Non-TARP banks (4)	Difference (3)-(4) t-stat.
Panel A Earnings management measure 1 (EM1)						
Pre-TARP Y(-3,-1)	0.006	0.021	-0.015	-0.021	0.005	-0.026
Post-TARP Y(1,3)	-0.026	0.030	-0.056	-0.057	0.023	-0.080*
Difference Y(1,3)- Y(-3,-1)	-0.032	0.009	-0.041	-0.036	0.018	-0.054
Panel B Earnings management measure 2 (EM2)						
Pre-TARP Y(-3,-1)	-0.002	0.042	-0.045	-0.025	0.008	-0.033
Post-TARP Y(1,3)	-0.035	-0.010	-0.025	-0.013	0.003	-0.015
Difference Y(1,3)- Y(-3,-1)	-0.033	-0.052	0.019	0.012	-0.057	0.018
Panel C Firm-specific bank efficiency (FBE)						
Pre-TARP Y(-3,-1)	0.524	0.515	0.009	0.512	0.521	-0.009
Post-TARP Y(1,3)	0.500	0.526	-0.026	0.489	0.523	-0.035***
Difference Y(1,3)- Y(-3,-1)	-0.023	0.012	-0.035*	-0.024*	0.002	-0.026
Panel D Manager-specific bank efficiency (MBE)						
Pre-TARP Y(-3,-1)	0.462	0.472	-0.011	0.472	0.463	0.010
Post-TARP Y(1,3)	0.454	0.473	-0.019	0.461	0.486	-0.024*
Difference Y(1,3)- Y(-3,-1)	-0.007	0.001	-0.008	-0.011	0.023*	-0.034

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

Panel C shows that the difference of FBE between TARP and non-TARP bank holding companies during the post-TARP period is significantly negative (-0.035), which denotes that, from a firm-specific point of view, TARP banks are less efficient than non-TARP banks in three years after the TARP infusions. Panel D shows that the difference of MBE between TARP and non-TARP bank holding companies during the post-TARP period is negative and significant at 10% level (-0.024), which means that from a manager-specific point of view, TARP banks are less efficiency than non-TARP banks in three years after the TARP injection. Additionally, we find that TARP banks are less firm-specifically efficient (-0.024) during the post-TARP period compared with the pre-TARP period, and that non-TARP banks have a higher MBE (0.023) after the TARP infusion year compared with the pre-TARP period. Moreover, the difference in difference test results of FBE (-0.026) and MBE (-0.034) are both negative and insignificant. These findings suggest that TARP capital injections have no significant impact on recipients' firm-specific bank efficiency and manager-specific bank efficiency, supporting our Hypothesis 2 and 3.

4.6.2 Baseline analysis of EM, FBE and MBE around TARP

We conduct regression analysis to control for additional factors while studying the impact of TARP funds on banks' EM, FBE and MBE. Table 30, 31, 32 and 33 report regression results of EM1, EM2, FBE and MBE, respectively, where model (1) and (2) are derived from equation (34), model (3) and (4) express equation (35) and model (5) represents equation (36). Table 30's the coefficient of POST-TARP PERIOD (-0.168) for the TARP bank holding companies is negative and significant at the 10% level, suggesting that TARP bank holding companies may engage in less income-increasing EM after the TARP capital injections compared with their pre-TARP manipulation level. We do not observe the same pattern from commercial banks. The coefficients of POST-TARP PERIOD and TARP BANKS in models (2), (3) and (4) are statistically insignificant for both commercial banks and bank holding companies. These results indicate that after controlling for other firm factors, TARP does not affect non-TARP banks' EM1 in the long term. Moreover, TARP recipients do not have significantly different EM behaviour than non-TARP banks during both pre- and post-TARP periods.

In the whole sample model (5) for bank holding companies, the coefficient of POST-TARP PERIOD is -0.080 and significant at 5% level. This suggests that, in general, estimated bank holding companies engage in less upwards EM practices after TARP capital infusions. This pattern is not observed from commercial banks, indicating that estimated commercial banks' EM behaviour stays the same regardless of TARP. The coefficients of TARP BANK in model (5) are insignificant, indicating that, during the estimated periods, TARP banks conduct similar EM practices as non-TARP banks. More importantly, the coefficients for the interaction variable between TARP BANK and POST-TARP PERIOD are statistically insignificant as shown in model (5). These results suggest that TARP capital infusions do not affect recipients' earnings manipulation decisions, consistent with our Hypothesis 1 and our conclusions in section 4.6.1.

Table 31 presents the regression results of EM2, where the coefficients of TARP BANK and the interaction term of POST-TARP PERIOD and TARP BANK are statistically insignificant in all of our models. The coefficients of POST-TARP PERIOD are statistically insignificant in all of our models, except the coefficient for non-TARP bank holding companies (-0.113), which is negative and significant at the 10% level. These results suggest that, in general, both TARP and non-TARP banks do not change their EM behaviour in the long term after the TARP capital injection year compared to their pre-TARP behaviour. Additionally, TARP recipients do not have a significantly different EM behaviour during both pre- and post-TARP periods compared with non-TARP banks. Our findings also indicate that TARP capital infusions have no significant impact on recipients' earnings management behaviour. These results are consistent with our findings based on EM1.

Table 32 reports the multivariate analysis results of FBE. The coefficients of POST-TARP PERIOD in model (1) are insignificant but they are positive and significant at the 10% level in model (2). These results suggest that non-TARP banks have slightly better firm-specific bank efficiency post-TARP compared with the pre-TARP period, while FBE of TARP banks does not change significantly after TARP injections. The coefficients of TARP BANKS in model (3) and (4) are insignificant for commercial banks and bank holding companies. These results suggest that after controlling for additional factors, TARP recipients do not have significantly different firm-specific bank efficiency from non-TARP banks during both pre- and post-TARP periods.

As for the full-sample models (model (5)), the coefficients of POST-TARP PERIOD are significantly positive for both commercial banks (0.052) and bank holding companies (0.028), which means that estimated banks have a higher long-term FBE after the infusion of TARP funds. The coefficients of TARP BANKS in model (5) are insignificant, suggesting that TARP and non-TARP banks have comparable FBE among the entire estimated period. The interaction term' coefficients are also statistically insignificant, indicating that TARP has no impact on recipients' efficiency driven by banks' non-managerial characteristics. These results are consistent with our Hypothesis 2 as well as findings in section 4.6.2.

Table 30 TARP capital injections and earnings management index 1 (EM1).

This table reports regression results on EM1, where EM1 refers to a loan loss provision based earnings management indicator. The samples are all unbalanced panel datasets. Regressions are conducted on TARP banks, non-TARP banks, pre-TARP periods, post-TARP and the entire sample, respectively. Commercial banks and bank holding companies are analysed, respectively. The variable denoted POST-TARP PERIOD equals one for three years after the TARP infusion year and takes the value of zero for three years prior to the TARP capital infusion year. The variable denoted TARP BANK equals one if the bank is a TARP recipient; otherwise it takes the value of zero. The TARP BANK*POST-TARP PERIOD variable is an interaction between TARP BANK and POST-TARP PERIOD. The variable denoted Lag EM1 is the first lag of EM1, controlling for dynamic impacts. Several bank attribute indicators are applied as control variables in the regressions, including the natural logarithm of total assets (Ln(assets)), non-performing loans to gross loans ratio, returns to total assets ratio, liquid assets to total assets ratio and net charge offs to total loans ratio. Bank effects are controlled in the models when applicable and robust errors are used in all models. For instance, TARP BANK dummy has collinearity with the bank fixed effect in the regression, therefore, we do not control for the bank fixed effect in the whole sample model.

	Commercial banks					Bank holding companies				
	TARP banks (1)	Non-TARP banks (2)	Pre-TARP (3)	Post-TARP (4)	Whole sample (5)	TARP banks (1)	Non-TARP banks (2)	Pre-TARP (3)	Post-TARP (4)	Whole sample (5)
POST-TARP PERIOD	-0.055	-0.032			-0.039	-0.168*	0.047			-0.080**
TARP BANK			-0.032	0.010	-0.007			-0.026	-0.017	-0.031
TARP BANK* POST-TARP PERIOD					0.001					0.018
Ln(assets)	-0.299	-0.014	-0.0003	-0.003	0.001	-0.125	-0.369**	0.020	0.006	0.017
Non-performing loans to gross loans	0.009	0.006	0.033	0.042***	0.028**	0.073***	-0.034*	0.040	0.033*	0.040**
Returns to total assets	0.321***	0.215***	0.104**	0.288***	0.191***	0.270***	0.121**	0.072	0.027	0.042
Liquid assets to total assets	-0.021	0.016	-0.005	-0.010	-0.006	0.048	-0.0003	-0.005	0.008	-0.003
Net charge offs to total loans	0.195	0.128***	-0.056	0.116***	0.074**	0.071	0.239**	-0.111	-0.045	-0.058**
Lag EM1	-0.027	0.045	0.095	0.072	0.070	0.010	-0.176**	-0.247	0.113	0.105
Constant	6.565	0.032	-0.070	-0.352	-0.257	2.309	7.569**	-0.476	-0.218	-0.395
R-square	0.027	0.091	0.172	0.185	0.136	0.255	0.019	0.095	0.071	0.055
Obs.	219	546	373	392	765	567	792	639	720	1,359
Bank fixed effect	yes	yes	no	no	no	yes	yes	no	no	no
Robust error	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

Table 31 TARP capital injections and earnings management index 2 (EM2).

This table reports regression results on EM2, where EM2 refers to a loan loss reserve based earnings management indicator. The samples are all unbalanced panel datasets. Regressions are conducted on TARP banks, non-TARP banks, pre-TARP periods, post-TARP and the entire sample, respectively. Commercial banks and bank holding companies are analysed, respectively. The variable denoted POST-TARP PERIOD equals one for three years after the TARP infusion year and takes the value of zero for three years prior to the TARP capital infusion year. The variable denoted TARP BANK equals one if the bank is a TARP recipient; otherwise it takes the value of zero. The TARP BANK*POST-TARP PERIOD variable is an interaction between TARP BANK and POST-TARP PERIOD. The variable denoted Lag EM2 is the first lag of EM2, controlling for dynamic impacts. Several bank attribute indicators are applied as control variables in the regressions, including the natural logarithm of total assets (Ln(assets)), non-performing loans to gross loans ratio, returns to total assets ratio, liquid assets to total assets ratio and net charge offs to total loans ratio. Bank effects are controlled in the models when applicable and robust errors are used in all models. For instance, TARP BANK dummy has collinearity with the bank fixed effect in the regression, therefore, we do not control for the bank fixed effect in the whole sample model.

	Commercial banks					Bank holding companies				
	TARP banks (1)	Non-TARP banks (2)	Pre-TARP (3)	Post-TARP (4)	Whole sample (5)	TARP banks (1)	Non-TARP banks (2)	Pre-TARP (3)	Post-TARP (4)	Whole sample (5)
POST-TARP PERIOD	-0.241	-0.033			0.010	0.021	-0.113*			0.036
TARP BANK			-0.038	0.023	-0.032			-0.014	-0.019	-0.042
TARP BANK* POST-TARP PERIOD					0.036					0.034
Ln(assets)	0.338*	0.003	-0.024**	-0.017	-0.015*	0.451	0.187	0.019	0.015	0.018
Non-performing loans to gross loans	-0.017	-0.0002	-0.019	-0.005	-0.015	-0.038	-0.017	0.062	-0.021	-0.009
Returns to total assets	0.243***	0.138***	0.031	0.169***	0.086***	0.294	0.017	0.127	-0.038	0.000
Liquid assets to total assets	-0.001	0.027**	-0.001	-0.005	-0.002	-0.024	-0.020***	-0.002	0.014	0.001
Net charge offs to total loans	0.234*	0.039	0.043	0.079**	0.026	0.220	0.158**	-0.152	-0.003	-0.020
Lag EM2	-0.275***	-0.183*	-0.356***	0.038	-0.126	-0.371	-0.302***	0.066	-0.178	-0.137
Constant	-8.114*	-0.234	0.544*	0.191	0.282	-9.704	-3.954	-0.534	-0.194	-0.348
R-square	0.007	0.046	0.311	0.092	0.084	0.075	0.001	0.076	0.046	0.020
Obs.	219	546	373	392	765	567	792	639	720	1,359
Bank fixed effects	yes	yes	no	no	no	yes	yes	no	no	no
Robust error	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

Table 32 TARP capital injections and firm-specific bank efficiency (FBE).

This table reports regression results on FBE. The samples are all unbalanced panel datasets. Regressions are conducted on TARP banks, non-TARP banks, pre-TARP periods, post-TARP and the entire sample, respectively. Commercial banks and bank holding companies are analysed, respectively. The variable denoted POST-TARP PERIOD equals one for three years after the TARP infusion year and takes the value of zero for three years prior to the TARP capital infusion year. The variable denoted TARP BANK equals one if the bank is a TARP recipient; otherwise it takes the value of zero. The TARP BANK*POST-TARP PERIOD variable is an interaction between TARP BANK and POST-TARP PERIOD. The variable denoted Lag FBE is the first lag of FBE, controlling for dynamic impacts. Several bank attribute indicators are applied as control variables in the regressions, including the natural logarithm of total assets (Ln(assets)), non-performing loans to gross loans ratio, returns to total assets ratio, liquid assets to total assets ratio and net charge offs to total loans ratio. Bank effects are controlled in the models when applicable and robust errors are used in all models. For instance, TARP BANK dummy has collinearity with the bank fixed effect in the regression, therefore, we do not control for the bank fixed effect in the whole sample model.

	Commercial banks					Bank holding companies				
	TARP banks (1)	Non-TARP banks (2)	Pre-TARP (3)	Post-TARP (4)	Whole sample (5)	TARP banks (1)	Non-TARP banks (2)	Pre-TARP (3)	Post-TARP (4)	Whole sample (5)
POST-TARP PERIOD	0.028	0.027*			0.052***	0.021	0.024*			0.028***
TARP BANK			-0.004	-0.014	-0.006			0.000	-0.001	-0.003
TARP BANK* POST-TARP PERIOD					-0.002					0.006
Ln(assets)	0.120***	0.080***	0.001	0.021***	0.013***	0.091**	0.100***	0.017***	0.026***	0.029***
Non-performing loans to gross loans	-0.011	-0.003	0.001	-0.007**	-0.005**	-0.005	-0.004	-0.001	-0.008**	-0.006**
Returns to total assets	0.083***	0.059***	0.032**	0.056***	0.047***	0.044***	0.012	0.023***	0.021**	0.018***
Liquid assets to total assets	-0.010**	-0.002	0.002***	0.002	0.002	-0.008	0.002	0.000	0.001	-0.001
Net charge offs to total loans	0.009	0.000	-0.019**	-0.010***	-0.009***	-0.041***	-0.056***	-0.039***	-0.040***	-0.037***
Lag FBE	-0.120	0.045	0.686***	0.157***	0.267***	-0.009	0.179**	0.751***	0.195***	0.360***
Constant	-2.278***	-1.370**	0.124***	-0.029	0.047	-1.400*	-1.655**	-0.225**	-0.079	-0.266**
R-square	0.201	0.225	0.664	0.476	0.470	0.372	0.334	0.556	0.499	0.486
Obs.	179	488	317	350	667	456	669	534	591	1,125
Bank fixed effects	yes	yes	no	no	no	yes	yes	no	no	no
Robust error	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

Table 33 TARP capital injections and manager-specific bank efficiency (MBE).

This table reports regression results on MBE. The samples are all unbalanced panel datasets. Regressions are conducted on TARP banks, non-TARP banks, pre-TARP periods, post-TARP and the entire sample, respectively. Commercial banks and bank holding companies are analysed, respectively. The variable denoted POST-TARP PERIOD equals one for three years after the TARP infusion year and takes the value of zero for three years prior to the TARP capital infusion year. The variable denoted TARP BANK equals one if the bank is a TARP recipient; otherwise it takes the value of zero. The TARP BANK*POST-TARP PERIOD variable is an interaction between TARP BANK and POST-TARP PERIOD. The variable denoted Lag MBE is the first lag of MBE, controlling for dynamic impacts. Several bank attribute indicators are applied as control variables in the regressions, including the natural logarithm of total assets (Ln(assets)), non-performing loans to gross loans ratio, returns to total assets ratio, liquid assets to total assets ratio and net charge offs to total loans ratio. Bank effects are controlled in the models when applicable and robust errors are used in all models. For instance, TARP BANK dummy has collinearity with the bank fixed effect in the regression, therefore, we do not control for the bank fixed effect in the whole sample model.

	Commercial banks					Bank holding companies				
	TARP banks (1)	Non-TARP banks (2)	Pre-TARP (3)	Post-TARP (4)	Whole sample (5)	TARP banks (1)	Non-TARP banks (2)	Pre-TARP (3)	Post-TARP (4)	Whole sample (5)
POST-TARP PERIOD	-0.049	0.005			-0.001	0.038**	0.031			0.012
TARP BANK			0.002	-0.005	0.003			0.002	0.007	0.000
TARP BANK* POST-TARP PERIOD					-0.016					0.014
Ln(assets)	0.100	0.037	-0.003	-0.013***	-0.008***	0.010	-0.016	-0.0005	0.011	0.001
Non-performing loans to gross loans	0.003	-0.004	-0.010	-0.001	-0.001	-0.009**	-0.003	-0.011**	-0.002	-0.002
Returns to total assets	0.025	0.038***	0.024	0.057***	0.047***	0.033***	0.016	0.024***	0.016***	0.017***
Liquid assets to total assets	0.008	-0.003	-0.006***	-0.003	-0.004**	0.014	-0.034*	-0.004	-0.010	-0.004
Net charge offs to total loans	0.011	0.009	0.039*	0.026***	0.024***	0.007	-0.017*	-0.019*	-0.005	-0.007*
Lag MA	0.026	0.093*	0.405***	0.423***	0.463***	0.277***	0.318***	0.702***	0.554***	0.667***
Constant	-1.931	-0.435	0.314***	0.491***	0.370***	0.095	0.641	0.139	-0.018	0.120
R-square	0.059	0.098	0.341	0.512	0.423	0.467	0.379	0.586	0.534	0.552
Obs.	179	488	317	350	667	456	669	534	591	1,125
Bank fixed effects	yes	yes	no	no	no	yes	yes	no	no	no
Robust error	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

Table 34 Quantile regression model results on earnings management (EM), firm-specific bank efficiency (FBE) and manager-specific bank efficiency (MBE).

This table reports the 5th, 50th and 95th quantile regression results on EM, FBE and MBE. The samples are all unbalanced panel datasets. Regressions are conducted using the entire sample only. Commercial banks and bank holding companies are analysed, respectively. EM1, EM2, FBE and MBE are our dependent variables and their regression results are reported in panel A, B, C and D, respectively. EM1 is loan loss provision based earnings management indicator and EM2 is loan loss reserve based earnings management indicator. The variable denoted POST-TARP PERIOD equals one for three years after the TARP infusion year and takes the value of zero for three years prior to the TARP capital infusion year. The TARP BANK*POST-TARP PERIOD variable is an interaction between TARP BANK and POST-TARP PERIOD, where TARP BANK is a dummy equalling one if the bank is a TARP recipient; otherwise it takes the value of zero. Several bank attribute indicators are applied as control variables in the regressions, including the natural logarithm of total assets (Ln(assets)), non-performing loans to gross loans ratio, returns to total assets ratio, liquid assets to total assets ratio and net charge offs to total loans ratio. However, coefficients of control variables are not reported due to space limitation. Bank effects are fixed, robust errors and dynamic impacts are controlled in all models. TARP BANK dummy has collinearity with the bank fixed effect in the regression; therefore, we remove the TARP BANK variable in this analysis.

	Commercial banks			Bank holding companies		
	5th quantile	50th quantile	95th quantile	5th quantile	50th quantile	95th quantile
Panel A Quantile regression of Earnings Management measure 1 (EM1)						
POST-TARP PERIOD	-0.348	-0.035	0.436**	0.197	-0.002	0.301
TARP BANK* POST-TARP PERIOD	-0.072	-0.062	-0.061	-0.236	0.044	0.287
R-square	0.029	0.006	0.012	0.058	0.0001	0.008
Obs.	765	765	765	1,359	1,359	1,359
Fixed firm effects	yes	yes	yes	yes	yes	yes
Control variables	yes	yes	yes	yes	yes	yes
Panel B Quantile regression of Earnings Management measure 2 (EM2)						
POST-TARP PERIOD	-0.259	-0.027	-0.095	-0.240	-0.051*	0.242
TARP BANK* POST-TARP PERIOD	0.019	0.003	-0.008	0.072	0.022	-0.278
R-square	0.046	0.001	0.105	0.013	0.0002	0.080
Obs.	765	765	765	1,359	1,359	1,359
Fixed firm effects	yes	yes	yes	yes	yes	yes
Control variables	yes	yes	yes	yes	yes	yes
Panel C Quantile regression of Bank Efficiency (FBE)						
POST-TARP PERIOD	-0.008	0.023	0.037	0.122***	0.033***	-0.011
TARP BANK* POST-TARP PERIOD	-0.043	0.009	0.023	-0.070	-0.015	0.003
R-square	0.071	0.235	0.066	0.240	0.103	0.061
Obs.	667	667	667	1,125	1,125	1,125
Fixed firm effects	yes	yes	yes	yes	yes	yes
Control variables	yes	yes	yes	yes	yes	yes
Panel D Quantile regression of Managerial Ability (MBE)						
POST-TARP PERIOD	0.038	-0.029	0.081	0.046	0.034	0.005
TARP BANK* POST-TARP PERIOD	-0.039	-0.009	0.048	-0.023	-0.010	-0.018
R-square	0.026	0.015	0.010	0.055	0.256	0.074
Obs.	667	667	667	1,125	1,125	1,125
Fixed firm effects	yes	yes	yes	yes	yes	yes
Control variables	yes	yes	yes	yes	yes	yes

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

Table 33 shows the baseline analysis results of MBE. The coefficient of POST-TARP PERIOD (0.038) for TARP bank holding companies is significantly positive at the 5% level, which suggests that TARP banks are more efficient due to able managers after TARP infusions compared with their pre-TARP efficiency level. The coefficients of all of our other main variables of interest are statistically insignificant, denoting that after controlling for additional firm-specific factors, TARP and non-TARP banks have similar MBE during both pre- and post-TARP periods. Additionally, the insignificant interaction terms in the whole sample models suggest that TARP capital infusions have no impact on banks' manager-driven efficiency, consistent with our Hypothesis 3. The finding is also consistent with Montgomery and Takahashi (2014), who find that TARP fails to stimulate banks' lending. Our results further indicate that the failure may be due to lack of improvement in bank managers' abilities.

4.6.3 Robustness checks and sensitive tests

This section uses various models and specifications to test the sensitivity and robustness of our baseline analysis results.

Quantile regression

It is possible that the relationship between our main variables of interest and dependent variables are not linearly correlated and that the residuals from our baseline models are not normally distributed. Under these circumstances, the models that we presented in the previous sections would contain bias. Also, we would like to investigate the impact of TARP on banks' EM, FBE and MBE at different quantile levels of EM, FBE and MBE, instead of restricting results only based on the mean value of variables. Consequently, we conduct Quantile regressions using low, median and high quantiles of dependent variables, respectively, in this section. Specifically, we run regressions for 5th, 50th and 95th quantile of EM1, EM2, FBE and MBE, respectively and the results are reported in Table 34. The firm-specific effect is controlled in all regressions by removing means from variables. Therefore, the TARP bank dummy is dropped from all models due to the collinearity. We only report our main variables of interest in Table 33 due to the space limitation.

Panel A and panel B in Table 34 report Quantile regression results of EM1 and EM2, respectively. The coefficient of POST-TARP PERIOD at the 95th quantile of EM1 for commercial banks (0.436) is positive and significant at the 5% level, suggesting that extremely aggressive commercial banks engage in more upwards EM practices post-TARP, compared with their pre-TARP EM engagement. The coefficient POST-TARP PERIOD at the 50th quantile of EM2 for bank holding companies (-0.051) is negative and significant at the 10% level, indicating that bank holding companies have a median level of EM engagement manipulate earnings less during the post-TARP period compared with the pre-TARP period. The coefficients of POST-TARP PERIOD in all other models in Panel A and B are statistically insignificant, which suggests that commercial banks' and bank holding companies' EM behaviour stays the same at the post-TARP period, compared to their pre-TARP behaviour. The coefficients of the interaction terms are statistically insignificant in all models of Panel A and B, which is consistent with our findings in previous sections that TARP has no impact on firms' EM practices, which also supports our Hypothesis 1.

Quantile regression results of FBE and MBE are reported in Panel C and Panel D of Table 34, respectively. The coefficients of POST-TARP PERIOD on FBE are insignificant for commercial banks and 95th quantile of FBE for bank holding companies, whilst the coefficients on 5th (0.122) and 50th (0.033) quantile of FBE for bank holding companies are significantly positive. These findings suggest that commercial banks keep a similar level of FBE after the TARP infusion year. While table 32 shows a significantly positive association between POST-TARP PERIOD and FBE for bank holding companies, the results from Panel C Table 34 further imply that banks mainly drive the positive association with low and middle FBE. The coefficients of POST-TARP PERIOD on MBE are statistically insignificant among all quantile models, suggesting that the manager-driven bank efficiency does not change significantly between the pre- and post-periods. Furthermore, the coefficients of the interaction terms on FBE and MBE are statistically insignificant, which is consistent with our Hypothesis 2 and 3, as well as our previous findings that TARP has no impact on banks' firm-specific and manager-specific bank efficiency.

Overall, this section's findings suggest that estimated banks' EM, FBE and MBE have uncertain changes in the post-TARP period compared with the pre-TARP period. However, it is clear that, in the long term, TARP does not affect recipients' earnings management behaviour and their efficiency from both firm-specific and manager-specific perspectives.

Two-step GMM

The general method of moments (GMM) technique is a rigorous method to control potential endogenous problems and time-invariant effects. Our dynamic baseline regression given in equation (36) may contain dynamic endogeneity. Therefore, in this section, we use the two-step system GMM technique, as suggested by Arellano and Bover (1995), for robustness checks. We do not adopt instrumental variable regression models to control the endogeneity issues due to the difficulty of finding suitable instruments. GMM uses lag values of endogenous variables as instruments to eliminate potential endogenous issues. We adjust instruments based on the effectiveness and the over-identifying restrictions using Hansen's J tests, and fit appropriate instruments in our models accordingly. Additionally, we use the third and fourth lags of the dependent variable as instruments in each model. We further apply two-step GMM to make the standard covariance matrix robust to panel-specific autocorrelation and heteroscedasticity. We use robust errors to eliminate bias in the standard error. Finally, we use year dummies to control for the time-invariant effect in our models.

Table 35 General method of moments model (GMM) results on earnings management (EM), firm-specific bank efficiency (FBE) and manager-specific bank efficiency (MBE).

This table reports two-step GMM regression results on EM, FBE and MBE. The samples are all unbalanced panel datasets. Regressions are conducted using the entire sample only. Commercial banks and bank holding companies are analysed, respectively. EM1, EM2, FBE and MBE are our dependent variables, where EM1 is loan loss provision based earnings management indicator and EM2 is loan loss reserve based earnings management indicator. The variable denoted POST-TARP PERIOD equals one for three years after the TARP infusion year and takes the value of zero for three years prior to the TARP capital infusion year. The variable denoted TARP BANK equals one if the bank is a TARP recipient; otherwise it takes the value of zero. The TARP BANK*POST-TARP PERIOD variable is an interaction between TARP BANK and POST-TARP PERIOD. The variables denoted Lag EM1, Lag EM2, Lag FBE and Lag MBE are the first lag of EM1, EM2, FBE and MBE, respectively. These lag values are applied to control for dynamic impacts. Several bank attribute indicators are applied as control variables in the regressions, including the natural logarithm of total assets (Ln(assets)), non-performing loans to gross loans ratio, returns to total assets ratio, liquid assets to total assets ratio and net charge offs to total loans ratio. The third and fourth lags of the dependent variable are applied as instruments in each model, based on the effectiveness and the over-identifying restrictions from the Hansen's J tests. Year and bank effects are fixed and robust errors are controlled in all models. TARP BANK dummy has collinearity with the bank fixed effect in the regression, therefore, we remove the TARP BANK variable in this analysis.

	Commercial banks				Bank holding companies			
	EM1	EM2	FBE	MBE	EM1	EM2	FBE	MBE
POST-TARP PERIOD	0.071	0.149	-0.101*	0.084	0.804	-0.172	-0.013	0.030
TARP BANK	-0.017	-0.045	-0.009	0.007	0.013	-0.015	-0.0003	0.001
TARP BANK* POST-TARP PERIOD	0.037	0.087	-0.011	-0.024	-0.052	0.029	-0.007	0.010
Ln(assets)	0.004	-0.022*	0.022***	0.000	0.017	0.029	0.042***	0.010
Non-performing loans to gross loans	0.014	-0.028**	-0.008*	0.001	0.023	-0.009	-0.008**	-0.003
Returns to total assets	0.186***	0.130**	0.055***	0.033*	0.028	-0.002	0.025***	0.027***
Liquid assets to total assets	-0.007	-0.002	0.001	-0.0003	-0.007	0.002	-0.003	-0.006
Net charge offs to total loans	0.104**	0.132***	-0.018**	0.009	-0.014	-0.032	-0.054***	-0.012**
Lag EM1	0.248				0.231			
Lag EM2		0.158				-0.609***		
Lag BE			-0.011				0.070	
Lag MA				0.877				0.437***
Constant	-0.330		-0.047	-0.077	0.287	-0.632	-0.404**	0.047
Lag instruments	The third and fourth lags	The third and fourth lags	The third and fourth lags	The third and fourth lags	The third and fourth lags	The third and fourth lags	The third and fourth lags	The third and fourth lags
F-statistic	13.79***	3.62***	26.92***	12.09***	2.09***	5.90***	32.06***	12.36***
Obs.	765	765	667	667	1,359	1,359	1,125	1,125
Arellano-Bond test for AR(2)	0.05	-0.10	0.44	4.43	-0.24	-1.34	-1.12	-0.52
Hansen test	0.16	0.29	3.31	2.68	2.91	1.92	0.06	0.45
Year fixed effect	yes	yes	yes	yes	yes	yes	yes	yes
Bank fixed effect	yes	yes	yes	yes	yes	yes	yes	yes
Robust error	yes	yes	yes	yes	yes	yes	yes	yes

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

The results are reported in Table 35, where only results from the whole sample models are presented. The number of lags taken in each model is reported at the Lag instruments row. The coefficients of POST-TARP PERIOD and TARP BANK are statistically insignificant in all of our models, except the negative coefficient of POST-TARP PERIOD on commercial banks' FBE (-0.101), which is inconsistent with our results from previous sections. These results suggest that TARP banks do not perform differently from non-TARP banks among the whole sample period, and that banks' EM, FBE, and MBE may have uncertain changes after the TARP capital injections. Furthermore, we obtain insignificant coefficients of the interaction variables in all of our models, which means that after controlling for potential endogeneity, TARP does not show any impacts on banks' EM, FBE, and MBE in the long term. This finding supports all of our hypotheses and is consistent with our previous findings.

First-order autoregressive

Our baseline model, as shown in equation (36) is dynamic. Thus, it is possible that the disturbance term may have a first-order autoregressive problem. To address this concern, we apply a random-effects GLS model with a first-order autoregressive (AR(1)) disturbance suggested by Baltagi and Wu (1999) in this section. In other words, we estimate the model with a bank-specific linear trend. The results presented in Table 36 support all of our hypotheses and our previous findings that TARP does not impact banks' EM practices, non-managerial efficiency (firm-specific bank efficiency), and managerial efficiency (manager-specific bank efficiency) because the coefficients of the interaction term are insignificant. The coefficients of POST-TARP PERIOD on FBE are significantly positive for both commercial banks (0.052) and bank holding companies (0.041), consistent with the results obtained in Table 32. These results suggest that estimated banks have a higher long-term FBE after the infusion of TARP funds. The coefficients of POST-TARP PERIOD on EM and MBE are insignificant, indicating that TARP has no impact on estimated banks' EM and MBE. The insignificant coefficients of TARP BANK from this section support our previous findings that TARP banks do not perform differently from non-TARP banks among the whole sample period.

Table 36 Earnings management (EM), firm-specific bank efficiency (FBE) and manager-specific bank efficiency (MBE) with first-order autoregressive controls.

This table reports the regression results of EM, FBE and MBE from random-effect General Least Square (GLS) models controlling for first-order autoregressive (AR(1)) disturbance. The samples are all unbalanced panel datasets. Regressions are conducted using the entire sample only. Commercial banks and bank holding companies are analysed, respectively. EM1, EM2, FBE and MBE are our dependent variables, where EM1 is loan loss provision based earnings management indicator and EM2 is loan loss reserve based earnings management indicator. The variable denoted POST-TARP PERIOD equals one for three years after the TARP infusion year and takes the value of zero for three years prior to the TARP capital infusion year. The variable denoted TARP BANK equals one if the bank is a TARP recipient; otherwise it takes the value of zero. The TARP BANK*POST-TARP PERIOD variable is an interaction between TARP BANK and POST-TARP PERIOD. The variables denoted Lag EM1, Lag EM2, Lag FBE and Lag MBE are the first lag of EM1, EM2, FBE and MBE, respectively. These lag values are applied to control for dynamic impacts. Several bank attribute indicators are applied as control variables in the regressions, including the natural logarithm of total assets (Ln(assets)), non-performing loans to gross loans ratio, returns to total assets ratio, liquid assets to total assets ratio and net charge offs to total loans ratio.

	Commercial banks				Bank holding companies			
	EM1	EM2	FBE	MBE	EM1	EM2	FBE	MBE
POST-TARP PERIOD	-0.019	0.020	0.052***	0.022	-0.047	0.066	0.041***	0.016
TARP BANK	-0.024	-0.045	-0.006	-0.002	-0.019	-0.032	0.001	-0.004
TARP BANK* POST-TARP PERIOD	0.024	0.060	-0.009	-0.019	-0.009	0.010	-0.004	0.011
Ln(Assets)	0.006	-0.016	0.019***	-0.012***	0.017	0.024	0.041***	0.011
Non-performing loans to gross loans	0.031***	-0.016	-0.006**	-0.007**	0.033***	-0.010	-0.007***	-0.003
Returns to total assets	0.182***	0.105***	0.057***	0.037***	0.050***	0.012	0.022***	0.025***
Liquid assets to total assets	-0.008	-0.001	0.002	-0.004**	0.000	-0.0001	-0.003	-0.007
Net charge offs to total loans	0.046***	0.029	-0.012***	0.019***	-0.043***	-0.011	-0.050***	-0.007
Lag EM1	0.009				-0.151***			
Lag EM2		-0.236***				-0.410***		
Lag FBE			-0.016				0.107***	
Lag MBE				-0.016				0.398***
Constant	-0.345	0.293	0.057	0.711***	-0.425	-0.510	-0.393***	0.031
R-square	0.126	0.079	0.399	0.202	0.011	0.016	0.434	0.519
Obs.	765	765	667	667	1,359	1,359	1,125	1,125

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

TARP repayments

Our baseline analysis tests the impact of TARP capital injections on banks' EM, FBE and MBE in the following three years but the findings may be affected by the fact that TARP recipients gradually repay TARP funds after receiving the capital infusions. Additionally, the impact of TARP on EM, FBE and MBE may differ for TARP banks that take differing amounts of repayment time. In our dataset, 60 commercial banks and 95 bank holding companies repaid the full amount of TARP funds within the subsequent three years (i.e., fully repaid banks) compared with 22 commercial banks and 104 bank holding companies that only repaid a portion or did not repay at all in the following three years (i.e., non-fully repaid banks). TARP repayments may influence public confidence in corresponding banks, therefore, affecting banks' operating earnings and efficiency. Consequently, this section estimates the impact of TARP repayments on the association between TARP capital infusions and bank attributes by inserting a repayment dummy in Equation (36). We name the dummy variable as TARP REPAYMENTS, which equals one for fully repaid banks and zero for non-fully repaid banks.

Table 37 Earnings management (EM), firm-specific bank efficiency (FBE) and manager-specific bank efficiency (MBE) with TARP repayments.

This table reports the regression results of EM, FBE and MBE from random-effect General Least Square (GLS) models controlling for TARP repayments. The samples are all unbalanced panel datasets and regressions are conducted using the entire sample only. Commercial banks and bank holding companies are analysed, respectively. EM1, EM2, FBE and MBE are our dependent variables, where EM1 is loan loss provision based earnings management indicator and EM2 is loan loss reserve based earnings management indicator. The variable denoted POST-TARP PERIOD equals one for three years after the TARP infusion year and takes the value of zero for three years prior to the TARP capital infusion year. The variable denoted TARP BANK equals one if the bank is a TARP recipient; otherwise it takes the value of zero. The TARP BANK*POST-TARP PERIOD variable is an interaction between TARP BANK and POST-TARP PERIOD and the variable denoted TARP REPAYMENTS is a dummy variable equals to one for fully repaid banks and zero for non-fully repaid banks. The variables denoted Lag EM1, Lag EM2, Lag FBE and Lag MBE are the first lag of EM1, EM2, FBE and MBE, respectively. These lag values are applied to control for dynamic impacts. Several bank attribute indicators are applied as control variables in the regressions including the natural logarithm of total assets (Ln(assets)), non-performing loans to gross loans ratio, returns to total assets ratio, liquid assets to total assets ratio and net charge offs to total loans ratio. Robust errors are controlled in all models.

	Commercial banks				Bank holding companies			
	EM1	EM2	FBE	MBE	EM1	EM2	FBE	MBE
POST-TARP PERIOD	-0.056	0.006	0.052***	-0.001	-0.082**	0.041	0.030***	0.009
TARP BANK	-0.006	-0.034	-0.005	0.001	-0.034	-0.043	-0.002	0.002
TARP BANK* POST-TARP PERIOD	0.009	0.041	-0.002	-0.014	0.028	0.043	0.005	0.014
TARP REPAYMENTS	-0.046	-0.029	0.007	-0.026*	-0.010	-0.037	-0.005	0.005
Ln(assets)	-0.021*	-0.018	0.013***	-0.008***	0.002	-0.012	0.029***	-0.001
Non-performing loans to gross loans	0.027*	-0.015	-0.005**	-0.002	0.038**	-0.011	-0.006**	-0.001
Returns to total assets	0.236***	0.095***	0.047***	0.048***	0.041	-0.002	0.018***	0.017***
Liquid assets to total assets	0.004	-0.0004	0.002	-0.003**	-0.014***	-0.012***	-0.001	0.000
Net charge offs to total loans	0.110***	0.032	-0.009***	0.025***	-0.061**	-0.023	-0.037***	-0.007*
Lag EM1	0.077		0.265***		0.110			
Lag EM2		-0.126				-0.145		
Lag FBE			0.265***				0.370***	
Lag MBE				0.456***				0.662***
Constant	0.210	0.361	0.041	0.397***	-0.067	0.293	-0.272*	0.158
R-square	0.141	0.080	0.470	0.427	0.056	0.024	0.490	0.549
Obs.	756	756	667	667	1,303	1,303	1,091	1,091
Bank fixed effect	no	no	no	no	no	no	no	no
Robust error	yes	yes	yes	yes	yes	yes	yes	yes

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

The results presented in Table 37 are highly consistent with our baseline results that the interaction term (TARP BANK* POSY-TARP PERIOD) is not statistically significant in all models. This finding suggests that TARP did not have a long-term impact on banks' EM, FBE and MBE after controlling for TARP repayments. We also find that the coefficients of

TARP REPAYMENTS are insignificant in almost all models, indicating that TARP repayments did not affect banks' EM, FBE and MBE either. We further run Equation (36) using fully repaid banks and non-fully repaid banks, respectively, to investigate whether a specific type of banks' TARP infusions could affect their long-term EM, FBE and MBE. Our results suggest no impact on both types of banks.[15]

Placebo tests

In our previous analyses, the pre-TARP period is set as three years prior to the TARP capital injection year and the post-TARP period is defined as three years following the TARP capital infusion year. However, the estimated years may be within the Global financial crisis (GFC) period, causing the impact of TARP on EM, FBE, and MBE to be insignificant. To mitigate this concern, a placebo test is applied. We redefine the pre-TARP period as four to six years prior to the TARP infusion year to avoid the GFC period, while keeping other variables and conditions constant in equation (36). The new variable is named POST-TARP PERIOD_ALT, which takes a value of one for the three years after the year that the bank received TARP funds or three years after the year that the control bank's corresponding TARP recipient received TARP funds. The dummy takes the value of 0 for four to six years before the year that the bank received TARP funds or the control bank's corresponding TARP recipient received TARP funds. We further generate the interaction term based on variables, TARP BANK, and POST-TARP PERIOD_ALT.

The results are reported in Table 38, where as expected, the coefficients of the interactions are statistically insignificant in all models, suggesting that after eliminating the potential impacts from GFC, TARP still shows no impact on banks' EM, FBE and MBE. This finding also implies that banks' earnings management decisions and efficiency do not frequently vary much and therefore do not change significantly due to TARP.

4.6.4 TARP infusion amount

The amount of TARP capital infusions (TARP AMOUNT) ranges from 1,601 million to 25,000 million for commercial banks, and 92.41 million to 6,599 million for bank holding companies, in our sample. This means that the amount of the TARP capital infusion varies to a large extent. Therefore, this section aims to study whether the TARP amount affects banks' EM, FBE and MBE in the long term. We do this by conducting random-effect GLS

[15] The results are reported in Appendix CII.

techniques in the post-TARP period using TARP banks only. Our primary variable of interest is TARP AMOUNT, which is the natural logarithm of the amount of TARP capital infusions, and the dependent variables are EM1, EM2, FBE and MBE, respectively. All control variables from previous models are included in our models, except the natural logarithm of total assets and the liquidity to total assets ratio. Because these two ratios are highly relevant to the TARP AMOUNT variable, as shown in Table 27.

Table 38 Earnings management (EM), firm-specific bank efficiency (FBE) and manager-specific bank efficiency (MBE) with alternative pre-TARP periods

This table reports the results of placebo tests. The samples are all unbalanced panel datasets and regressions are conducted using the entire sample only. Commercial banks and bank holding companies are analysed, respectively. EM1, EM2, FBE and MBE are our dependent variables, where EM1 is loan loss provision based earnings management indicator and EM2 is loan loss reserve based earnings management indicator. The variable denoted POST-TARP PERIOD_ALT equals one for three years after the TARP infusion year and takes the value of zero for four to six years prior to the TARP capital infusion year. The variable denoted TARP BANK equals one if the bank is a TARP recipient; otherwise it takes the value of zero. The TARP BANK*POST-TARP PERIOD_ALT variable is an interaction between TARP BANK and POST-TARP PERIOD_ALT. The variables denoted Lag EM1, Lag EM2, Lag FBE and Lag MBE are the first lag of EM1, EM2, FBE and MBE, respectively. These lag values are applied to control for dynamic impacts. Several bank attribute indicators are applied as control variables in the regressions including the natural logarithm of total assets (Ln(assets)), non-performing loans to gross loans ratio, returns to total assets ratio, liquid assets to total assets ratio and net charge offs to total loans ratio. Robust errors are controlled in all models.

	Commercial banks				Bank holding companies			
	EM1	EM2	FBE	MBE	EM1	EM2	FBE	MBE
POST-TARP PERIOD_ALT	0.057	0.100**	0.060***	0.005	-0.063	0.088	0.036***	0.014
TARP BANK	0.056	0.089**	0.001	-0.011	0.019	0.011	0.003	0.001
TARP BANK* POST-TARP PERIOD_ALT	-0.043	-0.071	-0.013	-0.0002	-0.039	-0.037	0.000	0.010
Ln(assets)	-0.005	-0.005	0.017***	-0.009***	-0.007	-0.014	0.025***	0.006
Non-performing loans to gross loans	0.051**	0.015	-0.008***	-0.004	0.036**	-0.022	-0.007***	0.000
Returns to total assets	0.286***	0.218**	0.044***	0.048***	0.017	-0.056*	0.016***	0.018***
Liquid assets to total assets	-0.008	-0.003	0.002	-0.004***	0.010*	0.018**	-0.002	-0.007
Net charge offs to total loans	0.061	0.042	-0.011***	0.026***	-0.052***	-0.006	-0.030***	-0.008*
Lag EM1	0.003				0.136**			
Lag EM2		-0.011				-0.129		
Lag FBE			0.201***				0.359***	
Lag MBE				0.385***				0.653***
Constant	-0.316	-0.218	-0.015	0.438***	0.123	0.343	-0.191*	0.003
R-square	0.143	0.115	0.483	0.344	0.066	0.057	0.533	0.576
Obs.	749	749	641	641	1,314	1,314	1,091	1,091
Bank fixed effect	no	no	no	no	no	no	no	no
Robust error	yes	yes	yes	yes	yes	yes	yes	yes

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

The results are reported in Table 39, where we find that the coefficients of TARP AMOUNT on EM indicators are mainly statistically insignificant in all models, except the coefficient (-0.045) on EM2 for bank holding companies, which shows significance slightly at the 10% level. The results suggest that the TARP infusion amount does not affect recipients' earnings management behaviour in the long term. The coefficient of TARP AMOUNT for FBE is significantly positive for both commercial banks (0.023) and bank holding companies (0.028), indicating that the amount of TARP infusions is positively associated with banks firm-specific bank efficiency in the long term. The impact of TARP AMOUNT on MBE for commercial banks is significantly negative (-0.015), whereas that for bank holding companies (0.014) is positive and significant at the 10% level. Harris, Huerta and Ngo (2013) document a significantly negative association between TARP AMOUNT and commercial banks' operational efficiency following the capital infusions. Therefore, our findings suggest that the adverse impact of TARP AMOUNT on commercial bank efficiency is due to the potential that bank managers are less likely to allocate TARP infusions efficiently when the TARP amount increases.

Table 39 General Least Square (GLS) models with TARP injection amount.

This table reports random-effects GLS models results of TARP capital injection amount on Earnings management (EM), firm-specific bank efficiency (FBE) and manager-specific bank efficiency (MBE). The samples are all unbalanced panel datasets. Regressions are conducted using the sample of TARP recipients during the post-TARP period only. Commercial banks and bank holding companies are analysed, respectively. EM1, EM2, FBE and MBE are our dependent variables, where EM1 is loan loss provision based earnings management indicator and EM2 is loan loss reserve based earnings management indicator. The variable denoted TARP AMOUNT is the natural logarithm of the amount of TARP capital infusions. The variables denoted Lag EM1, Lag EM2, Lag FBE and Lag MBE are the first lag of EM1, EM2, FBE and MBE, respectively. These lag values are applied to control for dynamic impacts. Several bank attribute indicators are applied as control variables in the regressions, including non-performing loans to gross loans ratio, returns to total assets ratio and net charge-offs to total loans ratio. Some control variables are dropped due to the multicollinearity. Robust errors are controlled in all models.

	Commercial banks				Bank holding companies			
	EM1	EM2	FBE	MBE	EM1	EM2	FBE	MBE
TARP AMOUNT	-0.022	-0.013	0.023***	-0.015***	0.027	-0.045*	0.028***	0.014*
Non-performing loans to gross loans	0.028*	-0.021	-0.009***	-0.001	0.043***	-0.039*	-0.008**	-0.007**
Returns to total assets	0.286***	0.163***	0.061***	0.053***	0.203***	0.024	0.057***	0.022*
Net charge offs to total loans	0.154**	0.115*	-0.015	0.028**	0.044	0.014	-0.029**	0.007
Lag EM1	0.099				0.175**			
Lag EM2		-0.151				-0.157		
Lag FBE			0.174***				0.153**	
Lag MBE				0.254***				0.495***
Constant	-0.329**	-0.130	0.336***	0.356***	-0.223*	0.313	0.371***	0.207***
R-square	0.234	0.187	0.642	0.378	0.219	0.111	0.510	0.510
Obs.	183	183	144	144	397	395	282	282
Robust error	yes	yes	yes	yes	yes	yes	yes	yes

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

We then conduct two-step system GMM techniques to address the potential dynamic endogenous problems in our baseline models similar to the model applied in the two-step GMM part of section 4.6.3. The results are reported in Table 40, where the number of lagged instruments taken in each model is shown at the Lag Instruments row. The robust error is applied, and time- and firm-invariant impacts are controlled in all of our models. Our instruments are selected based on the effectiveness and the over-identifying restrictions using Hansen's J tests.

Table 40 General method of moments model (GMM) results with TARP injection amount.

This table reports two-step system GMM models results of TARP capital injection amount on Earnings management (EM), firm-specific bank efficiency (FBE) and manager-specific bank efficiency (MBE). The samples are all unbalanced panel datasets. Regressions are conducted using the sample of TARP recipients during the post-TARP period only. Commercial banks and bank holding companies are analysed, respectively. EM1, EM2, FBE and MBE are our dependent variables, where EM1 is loan loss provision based earnings management indicator and EM2 is loan loss reserve based earnings management indicator. The variable denoted TARP AMOUNT is the natural logarithm of the amount of TARP capital infusions. The variables denoted Lag EM1, Lag EM2, Lag FBE and Lag MBE are the first lag of EM1, EM2, FBE and MBE, respectively. These lag values are applied to control for dynamic impacts. Several bank attribute indicators are applied as control variables in the regressions, including non-performing loans to gross loans ratio, returns to total assets ratio and net charge offs to total loans ratio. Some control variables are dropped due to the multicollinearity. Different lags of the dependent variable are selected based on the effectiveness and the over-identifying restrictions using Hansen's J tests, which is reported at Lag instruments. Year and bank effects are fixed and robust errors are controlled in all models.

	Commercial banks				Bank holding companies			
	EM1	EM2	FBE	MBE	EM1	EM2	FBE	MBE
TARP AMOUNT	-0.019	-0.011	0.031***	-0.011	-0.041	-0.061*	0.023***	0.022
Non-performing loans to gross loans	0.012	-0.027	-0.012**	0.003	0.036***	-0.026*	-0.004	-0.011***
Returns to total assets	0.255***	0.195***	0.060***	0.046***	0.249***	0.122***	0.028	0.031*
Net charge offs to total loans	0.107**	0.152**	-0.023*	0.017	0.063	0.062	-0.038	0.009
Lag EM1	0.226				0.157			
Lag EM2		-0.146				-0.690***		
Lag BE			-0.001				0.514	
Lag MA				0.245*				0.208
Constant	-0.135	0.137	0.399***	0.334***	0.023	0.394**	-0.182	0.371***
Lag instruments	The second and further lags	The second and the third lags	The second and further lags	The second and further lags	The second and further lags	The third and further lags	The third and further lags	The second and further lags
F-statistic	4.99***	6.00***	17.36***	2.26**	3.66***	53.34***	13.35***	11.75***
Obs.	183	183	144	144	397	395	282	282
Arellano-Bond test for AR(2)	1.18	1.29	0.88	-0.91	-1.01	-0.52	-0.98	0.76
Hansen test	8.49	8.61	9.74	18.81	10.02	12.12	14.08	14.18
Year fixed effect	yes	yes	yes	yes	yes	yes	yes	yes
Bank fixed effect	yes	yes	yes	yes	yes	yes	yes	yes
Robust error	yes	yes	yes	yes	yes	yes	yes	yes

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

The results show that the coefficients of TARP AMOUNT on FBE are significantly positive for commercial banks (0.031) and bank holding companies (0.023). We also observe a negative impact of TARP AMOUNT on bank holding companies' EM2 at a 10% significant level, while the coefficients of TARP AMOUNT on the rest of the EM indicators are statistically insignificant. These results are consistent with the results presented in Table 39. The coefficients of MBE are insignificant for both commercial banks and bank holding companies, which is insignificant with our findings from Table 39. Overall, our results from GMM models suggest that after controlling for potential endogeneity, TARP AMOUNT is found to positively affect TARP recipients' long-term firm-specific bank efficiency. Additionally, the amount of TARP capital infusions has no impact on TARP recipients' income-increasing EM activities and their manager-specific bank efficiency in the long term.

4.6.5 Selection bias

In this section, we employ a Heckman (1976) two-step technique to correct the potential selection bias introduced by the bank and government choices about TARP recipients, by incorporating TARP decisions into econometric estimations following Berger and Roman (2017) and Berger, Makaew and Roman (2019). We first model the likelihood of a bank receiving TARP funds by regressing the TARP BANK dummy on the natural logarithm of assets, the total loans to total assets ratio, the liquid assets to deposits & money market funding ratio, and the regular tier 1 capital ratio, in two years prior to the TARP infusion using a Probit model. The GMM model also controls for the endogeneity caused by missing time-invariant factors. The first-step Heckman approach results are reported in Table 41 for commercial banks and bank holding companies, respectively. Then the inverse mills ratio is calculated accordingly and employed in the second-step Heckman approach.

The results from the second step are also displayed in Table 41, where model (1) studies the impact of TARP on recipients' EM, FBE and MBE in the long run, whilst model (2) investigates the association between the amount of TARP capital infusions and recipients' EM, FBE and MBE in the post-TARP period. The coefficients of TARP BANK are statistically insignificant in all of our models, suggesting that TARP banks do not have distinct EM, FBE and MBE from non-TARP banks among the estimated period. Our main variable of interest in model (1) is the interaction variable; the coefficients of the variable are statistically insignificant in all of our models. This finding supports our previous findings and our hypothesis that TARP capital infusions have no impact on banks' EM, FBE and MBE in the long term. We also find that the coefficients of TARP AMOUNT on FBE are significantly positive for commercial banks (0.030) and bank holding companies (0.021). These results highly support our findings in section 4.6.4 that commercial banks and bank holding companies that receive larger amounts of TARP funds have better firm-specific bank efficiency in the next three years after the capital infusions. The coefficients of TARP AMOUNT on EM are insignificant in most models, which is consistent with the results reported in section 4.6.4. The coefficient of MBE is negatively significant at the 10% level for commercial banks and is statistically insignificant for bank holding companies. These results are inconsistent with our findings from Table 39 and 40, suggesting that TARP AMOUNT has an unclear impact on recipients' manager-specific bank efficiency.

Table 41 Heckman two-step model (GMM) results on earnings management (EM), firm-specific bank efficiency (FBE) and manager-specific bank efficiency (MBE).

This table reports Heckman two-step regression results. The samples are all unbalanced panel datasets. The variable denoted TARP BANK equals one if the bank is a TARP recipient; otherwise it takes the value of zero. TARP BANK is regressed using a Probit model at the first step on the natural logarithm of total assets (Ln(assets)), total loans to total assets ratio, liquid assets to deposits & money market funding ratio and regular tier 1 capital ratio, two years prior to the TARP infusions. In the second step, the dependent variables are EM, FBE and MBE, respectively, where EM1 is loan loss provision based earnings management indicator and EM2 is loan loss reserve based earnings management indicator. TARP BANK, POST-TARP PERIOD and TARP BANK*POST-TARP PERIOD are used as our main variables of interests in regressions (1) and TARP AMOUNT is applied as a main variable of interests in regressions (2). Regression models (1) are conducted using the entire sample and regression models (2) are conducted using the sample of TARP recipients during the post-TARP period only. Commercial banks and bank holding companies are analysed, respectively. The variable denoted POST-TARP PERIOD equals one for three years after the TARP infusion year and takes the value of zero for three years prior to the TARP capital infusion year. The TARP BANK*POST-TARP PERIOD variable is an interaction between TARP BANK and POST-TARP PERIOD. The variables denoted Lag EM1, Lag EM2, Lag FBE and Lag MBE are the first lag of EM1, EM2, FBE and MBE, respectively. These lag values are applied to control for dynamic impacts. Several bank attribute indicators are applied as control variables in the regressions accordingly, including the natural logarithm of total assets (Ln(assets)), non-performing loans to gross loans ratio, returns to total assets ratio, liquid assets to total assets ratio and net charge offs to total loans ratio. The inverse mill ratios obtained from the first-step Heckman models are applied as an explanatory variable in the second step and robust errors are controlled in all of the second-step regressions.

	Commercial banks									Bank holding companies								
	First step	Second step								First step	Second step							
	TARP BANK	EM1		EM2		FBE		MBE		TARP bank	EM1		EM2		FBE		MBE	
		(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)		(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
TARP AMOUNT			-0.026		-0.025		0.030***		-0.013*			-0.013		-0.055**		0.021***		0.005
POST-TARP PERIOD		-0.031		0.021		0.048***		0.006			-0.076**		0.041		0.025***		0.013	
TARP BANK		-0.008		-0.021		-0.001		-0.006			-0.044		-0.066		-0.003		-0.003	
TARP BANK* POST-TARP PERIOD		-0.007		0.002		-0.002		-0.013			0.018		0.038		0.005		0.012	
Ln(assets)	0.177***	-0.022		-0.022		0.015***		-0.016***		0.114	0.017		0.018		0.027***		0.001	
Non-performing loans to gross loans		0.029**	0.032**	-0.015	-0.021	-0.004*	-0.009***	-0.003	-0.0002		0.038**	0.050***	-0.013	-0.035	-0.005**	-0.007**	-0.002	-0.007**
Returns to total assets		0.198***	0.288***	0.087***	0.149***	0.045***	0.063***	0.049***	0.058***		0.049*	0.190***	0.013	-0.030	0.017***	0.050***	0.018***	0.035**
Liquid assets to total assets		0.003		0.002		0.001		-0.001			0.004	0.029	0.012		-0.002		-0.003	
Net charge offs to total loans		0.068**	0.105*	0.017	0.061	-0.009***	-0.015	0.023***	0.036***		-0.047**	0.040	-0.002	-0.054	-0.037***	-0.030**	-0.005	0.017
Inverse Mills ratio		-0.139**	-0.212	-0.047	-0.319	0.016	0.058*	-0.061	0.030		-0.075	0.197***	-0.121	-0.159	0.005	0.020	-0.010	-0.104***
Lag EM1		0.072	0.059								0.113							
Lag EM2				-0.128	-0.178								-0.136	-0.161				

Table 41 Continues

	Commercial banks									Bank holding companies								
	First step	Second step								First step	Second step							
	TARP BANK	EM1		EM2		FBE		MBE		TARP bank	EM1		EM2		FBE		MBE	
		(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)		(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Lag FBE						0.264***	0.095								0.389***	0.169**		
Lag MBE								0.452***	0.294***								0.666***	0.514***
Total loans to total assets ratio	0.020*									0.020**								
Liquid Assets to Deposits & Money Market Funding ratio	-0.019*									-0.057***								
Regular tier1 capital ratio	-0.010									-0.085***								
Constant	-5.663***	0.435	0.015	0.517	0.378	-0.022	0.278***	0.639***	0.273***	-2.614	-0.323	-0.324*	-0.238	0.572**	-0.255**	0.367***	0.136	0.294***
R-square (overall)		0.147	0.252	0.084	0.212	0.457	0.651	0.437	0.400		0.061	0.231	0.027	0.120	0.492	0.466	0.553	0.532
Wald chi2	26.12***									58.74***								
Obs.	311	757	174	757	174	659	128	659	128	534	1,333	347	1,333	348	1,107	243	1,107	243
Robust error	no	yes	yes	yes	yes	yes	yes	yes	yes	no	yes	yes	yes	yes	yes	yes	yes	yes

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

4.7 Summary and conclusion

The implementation of TARP had one major objective: to increase credit availability and improve the soundness and stability of the financial system during the period of global financial crisis. Among the important implications of TARP on banks' earnings management behaviour, is to shed light on any improvement over efficiency, because such TARP-like implementations in the future would hold greater financial economic and operational values. This chapter examines the impact of TARP on U.S. commercial banks and bank holding companies' earnings management practices, pure bank efficiency and manager-driven bank efficiency post-TARP. Using a sample of 82 commercial banks, 199 bank holding companies and 317 matched control banks from 2005 to 2013, we find that TARP did not impact banks' EM, FBE and MBE in the long term.

We also find that TARP banks did not perform differently from non-TARP banks pre-TARP, suggesting that TARP funds were not distributed based on the efficiency of banks neither their EM behaviour. Our evidence further shows that TARP amount was positively associated with recipients' post-TARP pure bank efficiency, however, had no impacts on the efficiency driven by the ability of managers.

Our findings suggest that TARP did not generate extra benefits to the banking industry, which means banks' long-term earnings management decisions and efficiency are quite stable. They can hardly be affected by government interventions in the long run. Our findings further imply that TARP rescued banks from distress but did not fundamentally change its recipients' performance compared to their counterparts, suggesting that TARP is an effective temporary rescue project. Our results do not support that moral hazard was accompanied with TARP in the long term. In addition, our evidence also suggests that regulators reinforce the scrutiny of distressed banks that receive relatively low amounts of funds, following future capital-injection programme to strengthen the banking industry.

Our research further suggests that investors pay more attention to banks that receive larger amount of capital infusions in future programmes, because they are likely to outperform other capital recipients, especially for bank holding companies. Overall, the evidence suggests that government bailouts amounts may matter to recipients in the long term, however, the bailout itself is unlikely to affect the whole financial system permanently. Overall, our findings draw attention of stakeholders, investors, regulators and policy makers to the consequences of government bailouts.

Similar to chapter 3, a fair amount of missing values has appeared in this chapter, where those values are mainly derived from the bank efficiency model, causing constrained data availability of firm-specific bank efficiency (FBE) and manager-specific bank efficiency (MBE). To minimize the side effects caused by the data availability, an unbalanced panel data setting has been adopted, which could help retain the majority of observations in the empirical models.

Chapter 5 Conclusion

This chapter comprises four sections. Section 5.1 summarizes the main findings of three articles. Section 5.2 presents the contributions of this research. Section 5.3 emphasises the research limitations and discusses possible future research avenues.

5.1 Summary of Findings

This thesis studies the earnings management (EM) behaviour of financial and non-financial firms. In Chapter 2, we test the unconditional effects of EM on firms' subsequent stock performance, where EM is measured by accrual-based earnings management (AEM) and real activities earnings management (REM) indicators. EM indicators are ranked by quintiles to capture their moderating impacts on firms' future stock performance. We apply holding period returns, market adjusted returns and risk-adjusted returns to capture firms' future stock performance. Difference in mean and difference in median tests are employed as a univariate analysis to compare the subsequent stock performance between firms from the top and bottom EM groups. Additionally, fixed-effect Ordinary Least Square (OLS) models are built as baseline tests to estimate whether firms from the extreme EM groups perform differently from firms that are assigned to other EM groups in the future.

Based on a panel data set of 9,859 US public corporations from 1990 to 2016, we find that both AEM and REM adversely affect subsequent firm performance under ordinary settings. To the extent that EM adds to the uncertainty in share valuations, it does not, however, compensate investors accordingly. We find that investors' reactions towards different EM approaches are diverse; therefore, price correction occurs at different future periods for earnings manipulators that use different EM methods. Our empirical results stay consistent after controlling for EM's endogeneity using two-stage least square regressions.

We also estimate the effectiveness of the association between firms' EM practices and their future stock returns. Using M-scores to identify firms' EM intentions, we are able to classify intentional manipulators from non-intentional firms. Then, the effectiveness of the association is examined by applying difference in mean tests of future stock returns based on AEM, REM and M-scores. Our results indicate that investors and regulators who use AEM, REM and M-scores individually to capture EM behaviour, are potentially misled.

As a result, we proposed a new EM measure in this chapter by interacting AEM and REM with M-scores, respectively, to better capture firms' EM activities and improve the signalling role of EM on future stock performance. Our results from further multivariate tests support our proposal that the new EM measure is more effective as to explain firms' future stock returns. Our findings are robust to reverse causality, falsification tests and are not sensitive to unbalanced data setting due to the delisting.

Then we estimate the EM behaviour among financial firms. We mainly examine the impact of Accounting managerial behaviour (AMB) on future bank performance in the U.S. commercial banking industry in Chapter 3, where AMB is the interaction of earnings management and bank efficiency (or managerial ability) indicators. To study the impact, we firstly rank and divide banks into three groups based on their EM, bank efficiency (BE) and managerial ability (MA) values. Then we generate AMB by interacting EM groups with BE and MA groups, respectively, to better explain subsequent bank performance.

Using an unbalanced panel data sample of 589 U.S. commercial banks over the period 1998-2017, we find a positive association between AMB and future bank performance. Our evidence suggests that, commercial banks that artificially boost earnings for short-term profits suffer from poor future performance, especially when they are not technically efficient or when the ability of their managers is low. In contrast, banks that artificially smooth current-period earnings to retain profits are found to perform better subsequently, especially when they are also technically efficient or when the banks have able managers. Our findings are not sensitive to sample selection bias, business-cycle effects, row effect of AMB, endogenous issues, economic recession effects and regulation implementations.

We also investigate the impact magnitude of AMB on bank performance by studying whether AMB can affect the association between bank size and subsequent bank performance. We investigate the effect by interacting the AMB dummies of extreme groups with the nature logarithm of bank size as our main variables of interest. Previous studies have documented a positive association between bank size and bank performance (see Köster and Pelster, 2017; Mamatzakis and Bermpei, 2016; Bakoush, Abouarab and Wolfe, 2018), whereas our results suggest that size effect differs for banks with superior and poor AMB. This finding highlights the importance of AMB in commercial banking studies by revealing that AMB can potentially dominate the size impacts on bank performance.

Finally, we conduct an event-based EM study in Chapter 4. The long-term impacts of Trouble Assets Relief Program (TARP) on U.S. commercial banks and bank holding companies' earnings management decisions and bank efficiency are examined. In this chapter, bank efficiency is further split into firm-specific bank efficiency (FBE) and manager-specific bank efficiency (MBE) as suggested by prior research, to study which factor-driven bank efficiency has been actually affected by the TARP programme. Commercial banks and bank holding companies are estimated respectively to eliminate regulation impacts. We take three-year pre- and post-TARP periods as our examining period, and the difference in mean tests are conducted to study whether banks' post-TARP EM behaviour, FBE and MBE have differed compared with their corresponding pre-TARP figures. Multivariate tests are further employed to eliminate the impact of other bank attributes on the association between TARP and our variables of interest.

Using a sample of 82 commercial banks, 199 bank holding companies and 317 matched control banks across the period 2005 to 2013, we find that TARP did not impact banks' EM, FBE and MBE in the long term. Our evidence further reveals that TARP banks did not perform differently from non-TARP banks pre-TARP, suggesting that TARP funds were not distributed based on the efficiency of banks neither their EM behaviour. Our empirical results are robust to various robustness checks using different estimation techniques to control for limitations from our baseline models caused by skewed variable distributions, endogeneity, global financial crisis effects, TARP repayments effects, self-selection bias and the first-order autoregressive problem in the error term.

Our figure shows that the amount of TARP infusions that were given to banks varies to a large degree, therefore, we then study whether the TARP amount affects banks' EM, FBE and MBE in the long term. Our evidence from dynamic general least square models (GLS) shows that the TARP amount is positively associated with recipients' post-TARP pure bank efficiency, however, has no impacts on the efficiency driven by the ability of bank managers. These findings are consistent after controlling for potential endogenous issues and selection bias.

5.2 Contributions

This thesis has several appealing contributions to the investigation of financial and non-financial firms' earnings management practices. Distinct contributions of each chapter are presented as follows.

Chapter 2 studies the explanatory power of non-financial firms' earnings management activities on their long-term stock returns using an updated dataset. Considering the literature suggesting that EM contributes to stock volatility (Chen, Huang and Jha, 2012 and Chen, Kim and Yao, 2017), we account for the variability caused by EM using risk-adjusted stock returns additional to holding period returns and market-adjusted returns, to evaluate long-term stock performance. The estimation of risk-adjusted returns provides further evidence regarding the poor subsequent stock performance of aggressive earnings manipulators, which breaks the efficiency market theory and points to the difficulty investors still face in assessing the real effects of earnings management.

Additionally, we find that using AEM, REM or M-scores as EM indicators individually, can hardly explain firms' long-term performance. In other words, stakeholders, investors and regulators who use AEM, REM and M-scores individually to capture firms' EM behaviour can be potentially misled. As a result, a new EM approach is introduced in this chapter by interacting M-scores with AEM and REM to add additional explanatory power towards subsequent stock returns of non-financial firms. The additional explanatory power of the new EM measure is proved via our comparative empirical analysis. Consequently, investors and regulators are suggested to incorporate firms' EM indicators with their EM intentions to better target firms' EM activities, reduce the information asymmetry and maintain the integrity of the financial system.

Based on the agency problem theory, there is a conflict of interest between a company's management and the company's stockholders. For instance, a manager's bonus is frequently related to a company's performance, however, when the company's revenue surpasses a certain threshold, managers may not be able to receive a desired bonus increase. In this case, managers may conduct income-decreasing EM activities to artificially move a part of the revenue into the following accounting year, which goes against stakeholders' instant benefits. Findings from chapter 2 can benefit shareholders by revealing managers' EM behaviour more accurately to reduce the short-term loss. Our findings would also assist researchers in establishing the true and certain effects of EM on investors' wealth.

Chapter 3 introduces a new variable called accounting managerial behaviour (AMB), which is an interaction of EM with BE and MA, respectively. This chapter provides theoretical and empirical evidence supporting that AMB can stabilize the impact of EM, BE and MA on future bank performance. Additionally, banks with a high level of AMB are found to outperform banks with poor AMB in the subsequent accounting year. This result suggests bank managers to be more cautious when making business decisions because short-term focused strategies could cost banks' long-term profits. The result further suggests managers to take their ability and bank efficiency into account when considering manipulating earnings, since banks' infrastructure, personnel and activities could jointly generate banks' prospects.

The importance of AMB on explaining subsequent bank performance is further highlighted in chapter 3 by documenting that AMB can dominate commercial banks' size effect on their performance in the following year. Previous studies have documented a positive association between bank size and bank performance (see Köster and Pelster, 2017; Meles, Porzio, Sampagnaro and Verdoliva, 2016; Mamatzakis and Bermpei, 2016; Bakoush, Abouarab and Wolfe, 2018). This chapter, however, suggests that after introducing AMB into the association between bank size and bank performance, the relationship changes. Our evidence shows that bank size has a positive impact on superior AMB banks' future bank performance, while the impact on poor AMB banks' future returns turns negative. The results are likely to be useful for academic researchers who are interested in analysing banks' financial fundamentals.

Overall, this chapter draws the attention of stakeholders, investors, regulators and policy makers onto bank fundamentals that are associated with fraudulent accounting statements, which could potentially assist to identify distressed and undervalued banks. Consequently, stakeholders would be able to regulate their existing shares and investors could adjust their investment portfolios accordingly. Regulators would be able to track banks' previous fraudulent activities from their performance and infrastructure, and policy makers could design better policies to make the financial market more efficient.

Chapter 4 identifies the feasibility of a government bailout programme named TARP by estimating its impact on commercial banks and bank holding companies' EM, FBE and MBE. The empirical evidence from this chapter supports the effectiveness of the TARP capital injection programme in the long term. In other words, we find that TARP assisted banks during the global financial crisis period and may only affect the recipients shortly compared with non-TARP recipients. Banks return to their normal business schedule after surviving from the economic recession, which means that this chapter does not suggest the existence of a long-term moral hazard phenomenon following the TARP infusions.

Additionally, this chapter studies two components of bank efficiency, firm-specific bank efficiency and manager-specific bank efficiency, suggested by Demerjian, Lev and McVay (2012). Our empirical results suggest that the amount of the TARP infusions only affect the firm-specific bank efficiency of TARP recipients rather than the manager-specific bank efficiency, and the impact on the firm-specific bank efficiency is positive. This finding suggests investors to pay more attention to banks that receive larger amounts of capital infusions in future programmes, because they are likely to outperform other capital recipients. The finding can also be viewed as an evidence that although the intervention may limit managers' behaviour in the short term, government interventions can hardly affect bank managers' operating ability in the long term. This chapter also presents a negative association between TARP amounts and bank holding companies' subsequent EM practices, suggesting regulators to reinforce the scrutiny of distressed banks that receive relatively low amounts of funds, following future capital-injection programmes to strengthen the integrity of the banking industry.

Overall, the evidence from chapter 4 suggests that government bailouts amounts may matter to recipients in the long term, however, the bailout itself is unlikely to affect the whole financial system permanently. Our findings could draw attention of stakeholders, investors, regulators and policy makers on the consequences of government bailouts to pursue the best of their profits under comparable circumstances in the future.

To sum up, the knowledge derived from this study provides additional methods to evaluate firms' earnings management behaviour, and to signal future performance. It highlights the importance of firms' earnings manipulation intentions and bank efficiency when signalling firms' future performance using earnings manipulation indicators. The study provides analysts and investors additional methods to predict subsequent firm/bank performance. It also provides methods that could further assist in better detecting firms' earnings management activities. Therefore, this thesis could enable analysts and investors to make more informed and conscious investment suggestions and decisions.

Regulators were concerned about the side effects caused by firms' accounting errors and fraudulent financial practices, thus the SOX act was implemented in 2002. Unfortunately, the firms' fraudulent financial practices, like earnings management, have not been fully eliminated. This study documents the long-term impact of earnings management on financial and non-financial firms' performance, therefore, may be of interest to regulators and policy makers who are concerned with the consequences of firms' earnings manipulation activities following the SOX act. Additionally, this study finds a negative association between firms' income-increasing earnings management and subsequent performance, indicating a long-term side effect of firms' aggressive earnings manipulation activities. As a result, regulators and policymakers are suggested to further constrain firms' income-increasing earnings management activities to maintain the efficiency and stability of financial markets.

This study also has important implications for firm/bank managers and shareholders. The study documents a negative impact of aggressive earnings management on the long-term firm performance, where the aggressive manipulations are often behaved to achieve short-term targets in order to generate short-term benefits. The evidence from this study, thus, reveals that artificially pursuing short-term earnings targets is likely to cost in long-term profits, which highlights a disadvantage of earnings management to managers and shareholders. According to the agency theory that is applied to explain the relationship between business principals and their agents, there may exist an agency problem that managers and shareholders have conflicts of interest. Consequently, shareholders are suggested to increase the scrutiny of firm managers' activities for the prospects of a company, and to achieve optimal bonuses in the long-term. Finally, this thesis draws the attention of stakeholders, investors, regulators and policy makers to the impact of government interventions on banks' accounting quality and efficiency.

5.3 Research Limitations and future research directions

In this section, we present the limitations and shortcomings that are acknowledged in this thesis and propose a number of possible directions for future research as follows.

First, quite a few observations in our analysis are missing due to the availability of data. In Chapter 2, for instance, there are only 24,579 observations of the abnormal discretionary expenses (ABDE), and 21,214 observations of the total shares outstanding held by CEOs out of more than 100,000 overall observations. Limited amount of observations could cause a low level of degree of freedom in analysis that could potentially lead to biased analysis results. Additionally, missing values also appear in Chapter 3 and 4, where those values are mainly derived from the bank efficiency model, which causes constrained data availability of managerial ability (MA) in Chapter 3, and firm-specific bank efficiency (FBE) and manager-specific bank efficiency (MBE) in Chapter 4. To minimize the side effects caused by the constrained data availability, this thesis has used unbalanced panel data setting, which could help retain the majority of observations in our empirical models.

Second, this thesis could still contain endogenous issues. Endogeneity is an issue that exists in quite a few empirical studies and it can hardly be fully eliminated. In Chapter 2, although we have used a two-stage least squared (2SLS) model to address the endogeneity of earnings management, the instruments that we choose are still controversial. Perfect instrumental variables are extremely hard to acquire. In Chapter 3 and Chapter 4, we use a General Method of Moments (GMM) model to address potential endogenous issues in our dynamic baseline models. However, the GMM model cannot capture the origin of the endogeneity, which makes the factors that cause the endogenous problems unclear.

Third, the indices that are used to build the M-score in Chapter 2 contains factors to capture firms' EM intentions as well as elements to detect firms' EM practices. The part of indices for detecting EM practices has not been removed from the M-score computation in this thesis due to the difficulty in restructuring the formula and allocating new weights to the indices. Therefore, using the M-score to fully represent firms' EM intentions requires further discussion. As a result, the measure of EM intention can be further improved in future studies by generating a new index incorporating only factors that are likely to drive firms' EM intentions. The factors could comprise but are not limited to sale changes, gross margin changes, leverage changes, peer performance difference changes, auditor changes and board member specifications.

Next, our thesis only focuses on financial and non-financial firms in the United States, thus the EM consequences that have been studied in Chapter 2 and 3 could be sample-specific. This means that the association we find could be driven by U.S. regulations, which makes our findings inapplicable to other regions and countries. Consequently, further work could consider expanding the sample size to investigate the unconditional EM consequences worldwide.

Finally, our thesis treats firms from different states of U.S. identically; however, firm location may affect their EM incentives and activities, because firms are also regulated at the state level in the United States. Therefore, future studies could also consider examining whether firm location could affect the impact of EM on financial and non-financial firms' subsequent performance.

Appendix A Supplement to Chapter 2

Appendix AI Variable Description

Panel A Variables for the M-score model

DSRI_t	$(\frac{\text{Net receivables}_t[rect]}{Sales_t[sale]})/(\frac{\text{Net receivables}_{t-1}}{Sales_{t-1}})$, Data source: Compustat.
GMI_t	$(\frac{Sales_{t-1}[sales]-COGS_{t-1}[cogs]}{Sales_{t-1}})/(\frac{Sales_t-COGS_t}{Sales_t})$, Data source: Compustat.
AQI_t	$(1-\frac{Current\ assets_t[act]+PP\&E_t[ppent]}{Total\ assets_t[at]})/(1-\frac{Current\ assets_{t-1}+PP\&E_{t-1}}{Total\ assets_{t-1}})$, Data source: Compustat.
SGI_t	$Sales_t[sale]/Sales_{t-1}$, Data source: Compustat.
DEPI_t	$(\frac{Depreciation_{t-1}[dp-am]}{Depreciation_{t-1}+PPE_{t-1}[ppent]})/(\frac{Depreciation_t}{Depreciation_t+PPE_t})$, Data source: Compustat.
SGAI_t	$(\frac{\text{SG\&A expense}_t[xsga]}{Sales_t[sale]})/(\frac{\text{SG\&A expense}_{t-1}}{Sales_{t-1}})$, Data source: Compustat.
TATA_t	$\frac{IBX_t[ib]-CFO_t[oancf]}{Total\ assets_t[at]}$, Data source: Compustat.
LVGI_t	$(\frac{LTD_t[dltt]+Current\ liabilities_t[lct]}{Total\ assets_t[AT]})/(\frac{LTD_{t-1}+Current\ liabilities_{t-1}}{Total\ assets_{t-1}})$, Data source: Compustat.

Panel B Variables for regressions

$Longterm\ performance_{i,t}$	represents 12-month, 24-month or 36-month stock performances at year t. The stock performances are measured by HPRs, MARs and M2, respectively. The calculations of HPRs, MARs and M2 are provided in the main paper. Data source: CRSP.
$lag(longterm\ performance)_{i,t}$	represents the first lag of the $Longterm\ performance_{i,t}$.
$Earnings\ management_{i,t}$	takes a range of values based on DA, ABCFO, ABPC and ABDE, respectively, at year t. Continuous and dummy variables of DA, ABCFO, ABPC and ABDE are applied. The continuous variables of DA, ABCFO, ABPC and ABDE are computed in the main paper. The dummy variables include $Dummyda\_highest_{i,t}$, $Dummyda\_lowest_{i,t}$, $Dummyabcfo\_highest_{i,t}$, $Dummyabcfo\_lowest_{i,t}$, $Dummyabpc\_lowest_{i,t}$, $Dummyabpc\_lowest_{i,t}$, $Dummyabde\_highest_{i,t}$, $Dummyabde\_lowest_{i,t}$. Data source: Compustat.
$Dummyda\_highest_{i,t}$	is a dummy variable that equals to one for firms in the highest quintile group of DA at year t, zero otherwise.
$Dummyda\_lowest_{i,t}$	is a dummy variable that equals to one for firms in the lowest quintile group of DA at year t, zero otherwise.
$Dummyabcfo\_highest_{i,t}$	is a dummy variable that equals to one for firms in the highest quintile group of ABCFO at year t, zero otherwise.
$Dummyabcfo\_lowest_{i,t}$	is a dummy variable that equals to one for firms in the lowest quintile group of ABCFO at year t, zero otherwise.
$Dummyabpc\_highest_{i,t}$	is a dummy variable that equals to one for firms in the highest quintile group of ABPC at year t, zero otherwise.
$Dummyabpc\_lowest_{i,t}$	is a dummy variable that equals to one for firms in the lowest quintile group of ABPC at year t, zero otherwise.
$Dummyabde\_highest_{i,t}$	is a dummy variable that equals to one for firms in the highest quintile group of ABDE at year t, zero otherwise.

$Dummyabde\_lowest_{i,t}$	is a dummy variable that equals to one for firms in the lowest quintile group of ABDE at year t, zero otherwise.
$Logsize_{i,t}$	is the natural logarithm of company's total assets[at] at year t. Data source: Compustat.
$Leverage_{i,t}$	measured as the book value of debt [dltt +dlc] divided by the sum of debt and equity [dltt+dlc+ceq+pstk] at year t. Data source: Compustat.
$ROA_{i,t}$	is return on assets, measured as the income before discontinued operations [ib] divided by lagged total assets [at] at year t. Data source: Compustat.
$Ownership_{i,t}$	is the ownership concentration at year t. Data source: Thomson Reuters Institutional (13f) Holdings.
$Institutionown_{i,t}$	is the ratio of total institutional ownership divided by total shares outstanding [instown_perc] at year t. Data source: Compustat.
$CEOown_{i,t}$	is the percentage of total shares outstanding held by CEO [shrown_excl_opts_pct] at year t. Data source: ExecuComp.
$CEOage_{i,t}$	is the age of the CEO [page] as reported in the annual proxy statement at year t. Data source: ExecuComp.
$Hightech_{i}$	is a dummy variable that equals to one for firms with SIC codes between 7370 and 7379. Data source: Compustat.
$Bigaudit_{i,t}$	is a dummy variable that equals to one if the firm is audited by any Big 5 or Big 4 firms at year t, zero otherwise. Data source: Compustat.
$BTM_{i,t}$	is book-to-market ratio, measured as book value of equity [ceq] divided by market value of equity [prcc_f × csho] at year t. Data source: Compustat.
$Loss_{i,t}$	equals one if the firms' net income [ni] is negative at year t, and zero otherwise. Data source: Compustat.
$Stock\ liquidity_{i,t}$	is captured by Amihud measure, denoted as the average value of monthly return to trading volume ratio at year t. Data source: CRSP. We dropped firm-years that have less than five observations. Data source: Compustat.

Panel C Instruments	
$LogR\&D_{i,t}$	is the natural logarithm of Research & Development expenditure [xrd] at year t. Data source: Compustat.
$\Delta PPE_{i,t}$	is the yearly change of company's property, plant and equipment value [ppegt] at year t. Data source: Compustat.
$Special\ items_{i,t}$	the sum of special items [spi] and extraordinary items [xi], divided by total assets [at] at year t. Data source: Compustat.

Appendix AII Earnings management, M-score and future risk-adjusted stock performance

This table reports coefficients of earnings management (EM) proxies and interactions from Ordinary Least Square (OLS) regressions. The dependent variables are long-term stock performance, measured by Sharpe ratio and Jensen alpha, respectively. The estimated period ranges from 12 months to 36 months, beginning from the year following the EM ranking (base) year. Panel A to Panel D report results based on different EM proxies, i.e., discretionary accruals, abnormal cash flow from operations, abnormal production costs and abnormal discretionary expenses, respectively. Models (1), (3), (5) and (7) use individual EM dummies and models (2), (4), (6) and (8) adopt EM interactions. The dummy_highest is valued one if the corresponding earnings management measure lies in its highest quintile (Q5), zero otherwise; and the dummy_lowest is valued one if the corresponding measure lies in its lowest quintile (Q1), zero otherwise. Year and industry effects are fixed, and the robust errors are used in all the models. Fama-French 48-industry identification codes are used to control for industry effects and all control variables are applied in all models.

		Jensen alpha			Sharpe ratio		
	Independent variables	12 months	24 months	36 months	12 months	24 months	36 months
Panel A Discretionary Accruals (DA)							
(1)	Dummyda_highest	-0.004***	-0.001***	-0.0003	-0.035***	-0.012***	-0.005*
	Observations	15,912	13,961	12,217	15,907	13,961	12,217
(2)	Dummyda_highest*M-dummy	-0.005**	-0.003**	-0.003**	-0.059***	-0.026**	-0.026***
	Observations	10,697	9,222	7,910	10,693	9,222	7,910
Panel B Abnormal Cash Flow from Operations (ABCFO)							
(3)	Dummyabcfo_lowest	-0.003**	-0.001	0.000	-0.036***	-0.011**	-0.003
	Observations	15,959	14,004	12,255	15,954	14,004	12,255
(4)	Dummyabcfo_lowest* M-dummy	-0.006	-0.004*	-0.003*	-0.060***	-0.029**	-0.017*
	Observations	10,699	9,223	7,910	10,695	9,223	7,910
Panel C Abnormal Production Costs (ABPC)							
(5)	Dummyabpc_highest	-0.001	-0.001	-0.0003	-0.017**	-0.007	-0.003
	Observations	15,209	13,403	11,747	15,204	13,403	11,747
(6)	Dummyabpc_highest* M-dummy	-0.008**	-0.003	-0.001	-0.060**	-0.028**	-0.005
	Observations	10,231	8,841	7,582	10,227	8,841	7,582
Panel D Abnormal Discretionary Expenses (ABDE)							
(7)	Dummyabde_lowest	0.000	-0.0004	0.000	-0.004	-0.010	-0.006
	Observations	4,744	4,113	3,545	4,741	4,113	3,545
(8)	Dummyabde_lowest* M-dummy	-0.005	-0.001	-0.004	-0.067	-0.024	-0.052**
	Observations	3,547	3,024	2,556	3,544	3,024	2,556
	Industry effect fixed	yes	yes	yes	yes	yes	yes
	Year effect fixed	yes	yes	yes	yes	yes	yes
	Robust errors	yes	yes	yes	yes	yes	yes
	Control variables	yes	yes	yes	yes	yes	yes

* indicates statistical significance at the 10% level.
** indicates statistical significance at the 5% level.
*** indicates statistical significance at the 1% level.

Appendix AIII Stock performance and future earnings management (EM)

This table reports reverse causality analysis results. The analysis uses Probit regressions, where the dependent variables are earnings management interactions, which are interacted aggressive EM dummies and M-dummy. The dummy_highest is valued one if the corresponding EM measure lies in its highest quintile (Q5), zero otherwise; and the dummy_lowest is valued one if the corresponding measure lies in its lowest quintile (Q1), zero otherwise. The main variables of interest are firms' stock performance measures including holding period returns (HPRs), market adjusted returns (MARs) and Modigliani risk-adjusted performance (M2). We control for the dynamic effects from EM interactions. Special items, nature logarithm of research and development expenditure (Log(R&D)), and changes in value of property, plant and equipment (ΔPPE) are applied as control variables and the definitions are presented in Appendix I. Year and industry effects are fixed, and the robust errors are used in all the models. Fama-French 48-industry identification codes are used to control for industry effects.

Independent variables	$\mathrm{Dummyda\_highest} * \mathrm{M} - \mathrm{dummy}_{t+1}$			$\mathrm{Dummyabcfo\_lowest} * \mathrm{M} - \mathrm{dummy}_{t+1}$			$\mathrm{Dummyabpc\_highest} * \mathrm{M} - \mathrm{dummy}_{t+1}$			$\mathrm{Dummyabde\_lowest} * \mathrm{M} - \mathrm{dummy}_{t+1}$		
HPR_t	0.114***			0.015			0.043***			0.048		
MAR_t		0.116***			0.017			0.044***			0.050	
$M2_t$			2.100			-0.159			3.389**			1.028
$\mathrm{Dummyda\_highest} * \mathrm{M} - \mathrm{dummy}_t$	0.269***	0.268***	0.288***									
$\mathrm{Dummyabcfo\_lowest} * \mathrm{M} - \mathrm{dummy}_t$				0.542***	0.542***	0.547***						
$\mathrm{Dummyabpc\_highest} * \mathrm{M} - \mathrm{dummy}_t$							0.608***	0.607***	0.622***			
$\mathrm{Dummyabde\_lowest} * \mathrm{M} - \mathrm{dummy}_t$										0.340*	0.340*	0.333*
$\mathrm{Special\ Items}_t$	-0.268***	-0.270***	-0.245***	-0.442***	-0.443***	-0.439***	-0.020	-0.020	-0.024	0.150	0.149	0.141
LogRD_t	-0.141***	-0.141***	-0.142***	-0.141***	-0.141***	-0.138***	-0.191***	-0.191***	-0.193***	-0.257***	-0.256***	-0.256***
$\Delta\mathrm{PPE}_t$	-0.0001***	-0.0001***	-0.0001***	-0.0001**	-0.0001**	-0.0001**	0.000	0.000	0.000	0.0001**	0.0001**	0.0001**
Constant	-1.602***	-1.535***	-1.535***	-1.822***	-1.818***	-1.809***	-2.339***	-2.325***	-2.340***	-2.197***	-2.184***	-2.149***
Log likelihood	-4170	-4169	-4152	-3176	-3176	-3136	-1890	-1890	-1871	-659	-659	-652
Chi-Square	607***	606***	550***	530***	531***	516***	468***	468***	467***	255***	256***	251***
Observations	21,493	21,493	21,366	21,503	21,503	21,376	20,769	20,769	20,699	8,582	8,582	8,537
Industry effect fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effect fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* indicates statistical significance at the 10% level.
** indicates statistical significance at the 5% level.
*** indicates statistical significance at the 1% level.

Appendix AIV management (EM) and stock performance

This table reports falsification test results. The analysis uses Ordinary Least Square (OLS) regressions, where the dependent variable is the stock performance, measured by holding period returns (HPRs), market adjusted returns (MARs) and Modigliani risk-adjusted performance (M2), respectively. The main variables of interest are EM interactions, which are interacted aggressive EM dummies and M-dummy. The dummy_highest is valued one if the corresponding EM measure lies in its highest quintile (Q5), zero otherwise; and the dummy_lowest is valued one if the corresponding measure lies in its lowest quintile (Q1), zero otherwise. The dynamic effects from stock returns are controlled.
Year and industry effects are fixed, and the robust errors are used in all the models. Fama-French 48-industry identification codes are used to control for industry effects and all control variables are applied in all models. The definitions of control variables are reported in Appendix I.

Independent variables	HPR_t				MAR_t				$M2_t$			
Dummyda_highest $*$ M $-$ dummy$_t$	0.077*				0.077*				0.0005			
Dummyabcfo_lowest $*$ M $-$ dummy$_t$		-0.030				-0.030				-0.001		
Dummyabpc_highest $*$ M $-$ dummy$_t$			0.070				0.070				0.001*	
Dummyabde_lowest $*$ M $-$ dummy$_t$				0.086				0.086				-0.001
HPR_{t-1}	-0.138***	-0.136***	-0.135***	-0.101***								
MAR_{t-1}					-0.138***	-0.136***	-0.135***	-0.101***				
$M2_{t-1}$									-0.096***	-0.096***	-0.095***	-0.084***
$Stock\ liquidity_t$	2.118**	2.122**	2.203**	5.230***	2.118**	2.122**	2.203**	5.227***	0.038**	0.038**	0.040*	0.092***
$Logsize_t$	-0.051***	-0.051***	-0.050***	-0.019***	-0.051***	-0.051***	-0.050***	-0.019***	0.000*	0.000*	0.000*	0.000**
$Leverage_t$	-0.042***	-0.042***	-0.041***	-0.045***	-0.042***	-0.042***	-0.041***	-0.045***	-0.001***	-0.001***	-0.001***	-0.001***
ROA_t	0.575***	0.585***	0.582***	0.396***	0.575***	0.585***	0.582***	0.396***	0.014***	0.014***	0.014***	0.010***
BTM_t	-0.154**	-0.154**	-0.150**	-0.213***	-0.154**	-0.154**	-0.150**	-0.213***	-0.004***	-0.004***	-0.003***	-0.006***
$Ownership_t$	-0.684**	-0.685**	-0.729**	-0.447	-0.682**	-0.683**	-0.727**	-0.444	-0.009**	-0.009**	-0.009**	-0.012**
$Institutionown_t$	-0.040	-0.042	-0.045	-0.048	-0.040	-0.043	-0.046	-0.048	0.001	0.001	0.001	0.001
$CEOown_t$	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	0.000	0.000	0.000	0.000
$Exeage_t$	-0.0005	-0.001	-0.0004	0.0002	-0.0005	-0.001	-0.0004	0.0002	0.000	0.000	0.000	0.000
$Bigaudit_t$	-0.035	-0.034	-0.028	-0.052*	-0.034	-0.034	-0.028	-0.052	-0.0004	-0.0004	-0.0004	-0.001
$Hightech_t$	-0.012	-0.013	-0.009	0.007	-0.012	-0.013	-0.008	0.007	0.001***	0.001***	0.001***	0.001
Constant	0.729***	0.739***	0.707***	0.627***	0.595***	0.605***	0.574***	0.507**	0.009***	0.009***	0.009***	0.013***
R-square	0.196	0.196	0.195	0.305	0.107	0.107	0.107	0.193	0.363	0.363	0.364	0.428
Chi-Square	2798***	2774***	2680***	1443***	700***	701***	700***	433***	3948***	3938***	3855***	1853***
Observations	11,970	11,972	11,404	3,981	11,970	11,972	11,404	3,981	11,947	11,949	11,382	3,973
Industry effect fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effect fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* indicates statistical significance at the 10% level.
** indicates statistical significance at the 5% level.
*** indicates statistical significance at the 1% level.

Appendix AV Analysis using a fiscal-year match

This table reports coefficients of earnings management (EM) proxies and interactions from Ordinary Least Square (OLS) regressions. The annual accounting data from COMPUSTAT and stock return data from CRSP are matched based on fiscal years. The dependent variable is the long-term stock performance, measured by holding period returns (HPRs), market adjusted returns (MARs) and Modigliani risk-adjusted performance (M2), respectively. The estimated period ranges from 12 months to 36 months, beginning from the year following the EM ranking (base) year. Panel A to Panel D report results based on different EM proxies, i.e., discretionary accruals, abnormal cash flow from operations, abnormal production costs and abnormal discretionary expenses, respectively. Models (1), (3), (5) and (7) use individual EM dummies and models (2), (4), (6) and (8) adopt EM interactions. The dummy_highest is valued one if the corresponding earnings management measure lies in its highest quintile (Q5), zero otherwise; and the dummy_lowest is valued one if the corresponding measure lies in its lowest quintile (Q1), zero otherwise. Year and industry effects are fixed, and the robust errors are used in all the models. Fama-French 48-industry identification codes are used to control for industry effects and all control variables are applied in all models.

		HPRs			MARs			M2		
	Independent variables	12 months	24 months	36 months	12 months	24 months	36 months	12 months	24 months	36 months
Panel A Discretionary Accruals (DA)										
(1)	Dummyda_highest	-0.056***	-0.068***	-0.090**	-0.054***	-0.067***	-0.087**	-0.002***	-0.001***	-0.0004***
	Observations	15,468	13,595	11,871	15,468	13,595	11,871	16,019	14,059	12,322
(2)	Dummyda_highest* M-dummy	-0.095***	-0.103**	-0.170***	-0.095***	-0.100**	-0.164**	-0.003***	-0.001***	-0.001***
	Observations	10,390	8,964	7,656	10,390	8,964	7,656	10,785	9,280	7,968
Panel B Abnormal Cash Flow from Operations (ABCFO)										
(3)	Dummyabcfo_lowest	-0.027	-0.058	0.020	-0.023	-0.057	0.026	-0.002***	-0.001***	-0.0002
	Observations	15,513	13,636	11,907	15,513	13,636	11,907	16,066	14,102	12,360
(4)	Dummyabcfo_lowest* M-dummy	-0.096*	-0.179***	-0.129	-0.089*	-0.174***	-0.115	-0.002**	-0.001*	-0.001*
	Observations	10,392	8,965	7,656	10,392	8,965	7,656	10,787	9,281	7,968
Panel C Abnormal Production Costs (ABPC)										
(5)	Dummyabpc_highest	-0.037**	-0.068***	-0.082**	-0.034**	-0.064**	-0.076**	-0.001***	-0.0004**	-0.0002
	Observations	14,798	13,057	11,415	14,798	13,057	11,415	15,315	13,498	11,847
(6)	Dummyabpc_highest* M-dummy	-0.158***	-0.125	-0.052	-0.147***	-0.112	-0.031	-0.003***	-0.001	-0.0003
	Observations	9,944	8,596	7,340	9,944	8,596	7,340	10,317	8,899	7,638
Panel D Abnormal Discretionary Expenses (ABDE)										
(7)	Dummyabde_lowest	-0.014	-0.078	-0.110	-0.007	-0.071	-0.104	-0.0001	-0.0004	-0.0003
	Observations	4,565	3,966	3,407	4,565	3,966	3,407	4,781	4,145	3,759
(8)	Dummyabde_lowest* M-dummy	-0.110	-0.217**	-0.168	-0.110	-0.216**	-0.165	-0.003	-0.002**	-0.001
	Observations	3,420	2,923	2,456	3,420	2,923	2,456	3,578	3,043	2,573
	Industry effect fixed	yes	yes	yes	yes	yes	yes	yes	yes	yes
	Year effect fixed	yes	yes	yes	yes	yes	yes	yes	yes	yes
	Robust errors	yes	yes	yes	yes	yes	yes	yes	yes	yes
	Control variables	yes	yes	yes	yes	yes	yes	yes	yes	yes

* indicates statistical significance at the 10% level.
** indicates statistical significance at the 5% level.
*** indicates statistical significance at the 1% level.

Appendix AVI Earnings management, M-score and long-term stock performance using Quantile regressions

Appendix VI Earnings management, M-score and long-term stock performance using Quantile regressions

This table reports coefficients of earnings management (EM) proxies and interactions from Quantile regressions. The dependent variable is the long-term stock performance, measured by holding period returns (HPRs), market adjusted returns (MARs) and Modigliani risk-adjusted performance (M2), respectively. The estimated period ranges from 12 months to 36 months, beginning from the year following the EM ranking (base) year. We estimate the 10th, 50th and 90th quantile of stock returns. Panel A to Panel D report results based on different EM proxies, i.e., discretionary accruals, abnormal cash flow from operations, abnormal production costs and abnormal discretionary expenses, respectively. Models (1), (3), (5) and (7) use individual EM dummies and models (2), (4), (6) and (8) adopt EM interactions. The dummy_highest is valued one if the corresponding earnings management measure lies in its highest quintile (Q5), zero otherwise; and the dummy_lowest is valued one if the corresponding measure lies in its lowest quintile (Q1), zero otherwise. Year and firm effects are fixed and all control variables are applied in all models.

		HPRs									MARs									M2								
	Independent variables	12 months			24 months			36 months			12 months			24 months			36 months			12 months			24 months			36 months		
	Quantile	10th	50th	90th	10th	50th	90th	10th	50th	90th	10th	50th	90th	10th	50th	90th	10th	50th	90th	10th	50th	90th	10th	50th	90th	10th	50th	90th
Panel A Discretionary Accruals (DA)																												
(1)	Dummyda_highest	-0.062***	-0.038***	-0.038	-0.073***	-0.083***	-0.043	-0.076***	-0.085***	-0.098	-0.059***	-0.036***	-0.036	-0.086***	-0.063***	-0.077	-0.088***	-0.104***	-0.121*	-0.002***	-0.001***	-0.002***	-0.003**	-0.002***	-0.001	-0.002*	-0.0005	-0.001
	Observations	17,742	17,742	17,742	13,961	13,961	13,961	12,217	12,217	12,217	17,742	17,742	17,742	13,961	13,961	13,961	12,217	12,217	12,217	15,907	15,907	15,907	13,961	13,961	13,961	12,217	12,217	12,217
(2)	Dummyda_highest* M-dummy	-0.154***	-0.070***	0.040	-0.158***	-0.174***	-0.003	-0.281***	-0.125**	0.123	-0.165***	-0.070***	0.030	-0.264***	-0.079**	0.064	-0.181**	-0.128**	0.173	-0.004**	-0.003***	-0.003**	-0.012***	-0.005**	0.003	-0.010***	-0.002	0.003
	Observations	12,122	12,122	12,122	9,222	9,222	9,222	7,910	7,910	7,910	12,122	12,122	12,122	9,222	9,222	9,222	7,910	7,910	7,910	10,693	10,693	10,693	9,222	9,222	9,222	7,910	7,910	7,910
Panel B Abnormal Cash Flow from Operations (ABCFO)																												
(3)	Dummyabcfo_lowest	-0.102***	-0.038***	0.009	-0.091***	-0.067***	-0.046	-0.105***	-0.102***	0.139	-0.081***	-0.046***	-0.007	-0.085***	-0.061***	-0.008	-0.085**	-0.070**	0.095	-0.003***	-0.001***	-0.002***	-0.006***	-0.004	0.001	-0.001	-0.001	0.002
	Observations	17,792	17,792	17,792	14,004	14,004	14,004	12,255	12,255	12,255	17,792	17,792	17,792	14,004	14,004	14,004	12,255	12,255	12,255	15,954	15,954	15,954	14,004	14,004	14,004	12,255	12,255	12,255
(4)	Dummyabcfo_lowest* M-dummy	-0.161***	-0.063**	-0.086	-0.075	-0.151***	-0.193	-0.155	-0.128*	0.059	-0.210***	-0.079***	-0.057	-0.231***	-0.152***	-0.101	-0.135	-0.094	0.321	-0.003	-0.002**	-0.003*	-0.004	-0.006**	-0.005	-0.003	-0.004**	0.002

	Observations	12,124	12,124	12,124	9,223	9,223	9,223	7,910	7,910	7,910	12,124	12,124	12,124	9,223	9,223	9,223	7,910	7,910	7,910	10,695	10,695	10,695	9,223	9,223	9,223	7,910	7,910	7,910
Panel C Abnormal Production Costs (ABPC)																												
(5)	Dummyabpc_highest	-0.059***	-0.032**	0.054*	-0.078***	-0.037**	0.004	-0.068***	-0.071***	0.031	-0.062***	-0.021**	0.024	-0.059***	-0.019	0.017	-0.033	-0.052**	0.005	-0.002***	-0.001***	-0.001	-0.006***	-0.0001	0.001	-0.002*	-0.001	0.000
	Observations	16,875	16,875	16,875	13,403	13,403	13,403	11,747	11,747	11,747	16,875	16,875	16,875	13,403	13,403	13,403	11,747	11,747	11,747	15,204	15,204	15,204	13,403	13,403	13,403	11,747	11,747	11,747
(6)	Dummyabpc_highest*M-dummy	-0.161**	-0.109***	-0.045	-0.178*	-0.090*	0.026	-0.167	-0.137**	0.175	-0.200***	-0.054	-0.077	-0.281***	-0.063	0.094	-0.153	-0.032	0.140	-0.003	-0.002**	-0.002*	-0.006	-0.002	0.004	-0.001	-0.002	0.002
	Observations	11,545	11,545	11,545	8,841	8,841	8,841	7,582	7,582	7,582	11,545	11,545	11,545	8,841	8,841	8,841	7,582	7,582	7,582	10,227	10,227	10,227	8,841	8,841	8,841	7,582	7,582	7,582
Panel D Abnormal Discretionary Expenses (ABDE)																												
(7)	Dummyabde_lowest	0.001	0.005	0.017	-0.016	-0.008	0.008	-0.042	-0.035	0.038	0.030	0.008	0.011	0.011	-0.010	0.076	0.001	-0.025	-0.040	-0.001	0.001	0.001	-0.003	-0.001	0.002	-0.001	-0.0004	0.003
	Observations	5,326	5,326	5,326	4,113	4,113	4,113	3,545	3,545	3,545	5,326	5,326	5,326	4,113	4,113	4,113	3,545	3,545	3,545	4,741	4,741	4,741	4,113	4,113	4,113	3,545	3,545	3,545
(8)	Dummyabde_lowest*M-dummy	-0.248	-0.007	-0.020	-0.027	-0.081	-0.403	-0.183	-0.174	-0.770**	-0.124	-0.024	-0.211*	0.067	-0.030	-0.562*	-0.209	-0.312**	-0.759*	-0.007	-0.002	-0.003	-0.0005	-0.003	-0.021**	-0.003	-0.004	-0.006
	Observations	4,037	4,037	4,037	3,024	3,024	3,024	2,556	2,556	2,556	4,037	4,037	4,037	3,024	3,024	3,024	2,556	2,556	2,556	3,544	3,544	3,544	3,024	3,024	3,024	2,556	2,556	2,556
	Firm effect fixed	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
	Year effect fixed	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
	Robust errors	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
	Control variables	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

* indicates statistical significance at the 10% level.
** indicates statistical significance at the 5% level.
*** indicates statistical significance at the 1% level.

Appendix B Supplement to Chapter 3

Appendix B Variable Description

Panel A Variables for earnings management computation

LLP_{it}	Loan loss provisions ratio, defined as the ratio of loan loss provisions to average loans of bank i at year t, Data source: Fitchconnect.
$LLP_{i,t-1}$	Loan loss provisions ratio of bank i at year $t-1$, Data source: Fitchconnect.
$Ln(assets)_{it}$	Nature logarithm of total assets of bank i at year t, Data source: Fitchconnect.
ΔNPA_{it}	Difference in the ratio of non-performing loans to average loans of bank i at year t, Data source: Fitchconnect.
$Chargeoffs_{it}$	Net charge-offs of bank i at year t, Data source: Fitchconnect.
LLR_{it}	Loan loss reserves ratio, defined as the ratio of loan loss reserves to average loans of bank i at year t, Data source: Fitchconnect.
$LLR_{i,t-1}$	Loan loss reserves ratio of bank i at year $t-1$, Data source: Fitchconnect.
$Aloans_{it}$	Average loans of bank i at year t, Data source: Fitchconnect.

Panel B Variables for managerial ability measurement

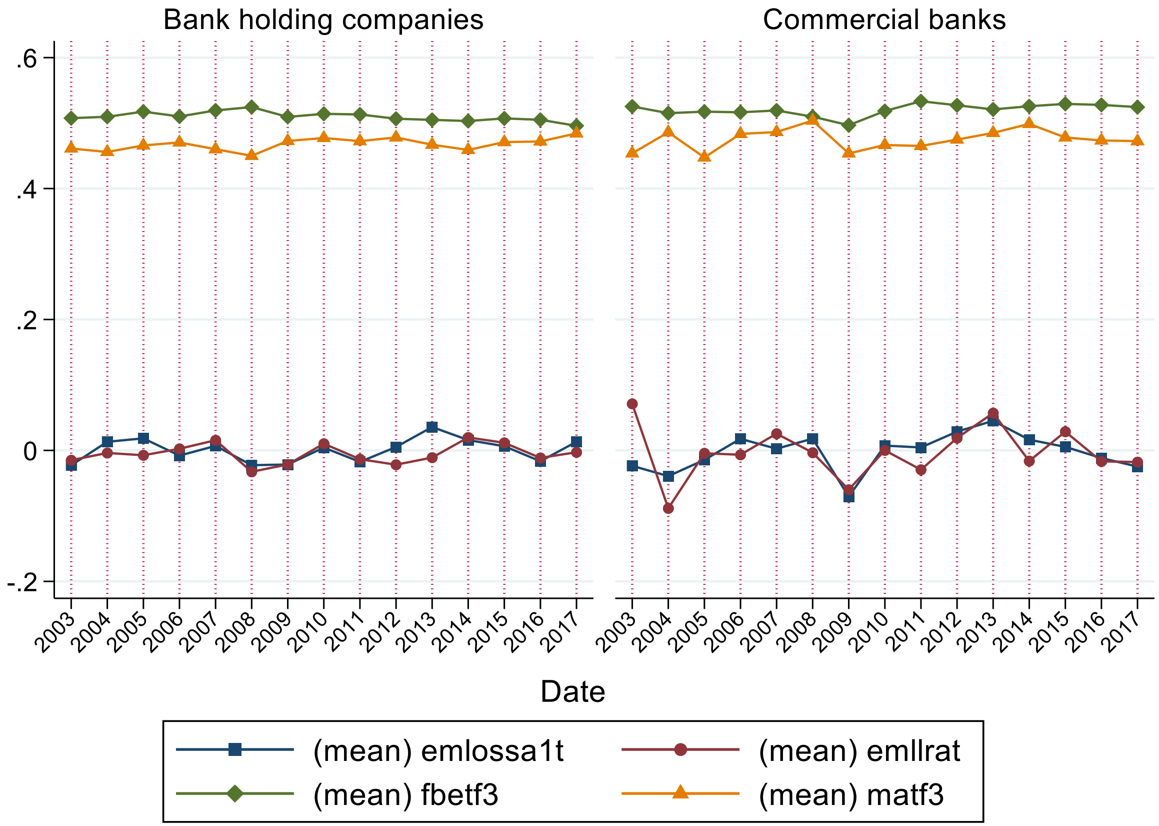
$BE_{i,t}$	Bank efficiency scores obtained from DEA approach of bank i at year t.
$Ln(employee)_{it}$	Nature logarithm of the number of employees of bank i at year t. Data source: Fitchconnect.
$Ln(age)_{it}$	Nature logarithm of the age of bank i at year t. Data source: Fitchconnect.
$Leverage_{it}$	Leverage ratio of bank i at year t, measured as total assets divided by total equity. Data source: Fitchconnect.
FCF_{it}	Asset liquidity indicator of bank i at year t, taking a value of one for positive cash flow years, zero otherwise. Data source: Fitchconnect.

Panel C Control variables for regressions

$Ln(deposits)_{i,t-1}$	Nature logarithm of deposits of bank i at year t+1. Data source: Fitchconnect.
FRG_{t+1}	The growth of the Federal fund rate at year t+1. Data source: Federal Reserve Bank database.
$HHI_{i,t+1}$	The weighted Herfindahl-Hirschmann index of bank i at year t+1, calculated using a bank's deposits in a given market as weights. Data source: Fitchconnect.
$NPLER_{i,t+1}$	The ratio of non-performing loans to the sum of equity and reserves of bank i at year t+1. Data source: Fitchconnect.
$LAWF_{i,t+1}$	The ratio of liquid assets to wholesale funding of bank i at year t+1. Data source: Fitchconnect.
$Charge-offs_{i,t+1}$	The ratio of net charge-offs to total loans of bank i at year t+1. Data source: Fitchconnect.
$ROA_{i,t+1}$	The net income to total assets ratio of bank i at year t+1. Data source: Fitchconnect.
$LATA_{i,t+1}$	The ratio of liquid assets to total assets of bank i at year t+1. Data source: Fitchconnect.
SOX	A dummy equals one for the period since 2002 in our sample, equals zero for years before 2002.
GFC	A dummy equals one for the period 2007 to 2009, equals zero for other years of our sample period.

Appendix C Supplement to Chapter 4

Appendix CI Banks' yearly earnings management (EM), firm-specific bank efficiency (FBE) and manager-specific bank efficiency (MBE)



Appendix CII General Least Square (GLS) models with TARP repayments for split samples.

This table reports the regression results of random-effect General Least Square (GLS) models on EM, FBE and MBE, for fully repaid TARP banks and non-fully repaid TARP banks, respectively. Fully repaid banks are those repaid the full amount of TARP funds in three years, whilst non-fully repaid TARP banks are those did not fully repay TARP funds in a subsequent three-year time. The samples are all unbalanced panel datasets and regressions are conducted using the entire sample only. Commercial banks and bank holding companies are analysed, respectively. EM1, EM2, FBE and MBE are our dependent variables, where EM1 is loan loss provision based earnings management indicator and EM2 is loan loss reserve based earnings management indicator. The variable denoted POST-TARP PERIOD equals one for three years after the TARP infusion year and takes the value of zero for three years prior to the TARP capital infusion year. The variable denoted TARP BANK equals one if the bank is a TARP recipient; otherwise it takes the value of zero. The TARP BANK*POST-TARP PERIOD variable is an interaction between TARP BANK and POST-TARP PERIOD. The variables denoted Lag EM1, Lag EM2, Lag FBE and Lag MBE are the first lag of EM1, EM2, FBE and MBE, respectively. These lag values are applied to control for dynamic impacts. Several bank attribute indicators are applied as control variables in the regressions including the natural logarithm of total assets (Ln(assets)) non-performing loans to gross loans ratio, returns to total assets ratio, liquid assets to total assets ratio and net charge offs to total loans ratio. Robust errors are controlled in all models.

	Commercial banks								Bank holding companies							
	EM1		EM2		FBE		MBE		EM1		EM2		FBE		MBE	
	Non-fully repaid banks	Fully repaid banks	Non-fully repaid banks	Fully repaid banks	Non-fully repaid banks	Fully repaid banks	Non-fully repaid banks	Fully repaid banks	Non-fully repaid banks	Fully repaid banks	Non-fully repaid banks	Fully repaid banks	Non-fully repaid banks	Fully repaid banks	Non-fully repaid banks	Fully repaid banks
POST-TARP PERIOD	0.027	-0.061	-0.017	0.011	0.075***	0.047***	-0.035	0.009	0.154	0.272**	0.071	-0.004	0.036***	0.027**	0.017	0.005
TARP BANK	0.053	-0.021	-0.020	-0.039	-0.006	-0.006	0.013	-0.006	-0.060	0.050	-0.003	-0.080	0.007	-0.017	0.003	0.003
TARP BANK* POST-TARP PERIOD	0.087	-0.033	0.039	0.015	-0.003	0.000	-0.022	-0.010	0.303	-0.109	-0.037	0.102	-0.008	0.008	0.004	0.018
Ln(assets)	-0.059**	0.000	-0.050***	0.003	0.009**	0.011***	0.002	-0.01***0	-0.383***	-0.399***	-0.007	0.000	0.030**	0.023***	-0.004	0.004
Non-performing loans to gross loans	0.005	0.029*	-0.034**	-0.003	-0.009***	-0.005*	0.007	-0.004	0.087***	0.097**	-0.020	0.016	-0.005*	-0.008**	-0.003*	0.002
Returns to total assets	0.258***	0.189***	0.194***	0.096***	0.062***	0.039***	0.058***	0.046***	0.095***	0.088	-0.028	0.033	0.016**	0.018**	0.013***	0.023***
Liquid assets to total assets	0.004	0.0003	0.014	-0.006	-0.010***	0.003***	0.000	-0.003*	-0.009**	0.006	-0.011***	-0.027	-0.005	-0.006	-0.001	0.010
Net charge offs to total loans	0.135	0.070**	0.210***	-0.026	-0.013**	-0.007*	0.018**	0.027***	-0.114***	-0.060	-0.009	-0.069	-0.033***	-0.034***	-0.004	-0.014**
Lag EM1	-0.038	0.098							-0.242***	-0.118*						
Lag EM2			0.038	-0.182*							-0.107	-0.273**				
Lag FBE					0.088	0.333***							0.359***	0.443***		
Lag MBE							0.363***	0.468***							0.651***	0.675***
Constant	1.035*	-0.210	0.914**	-0.090	0.225**	0.065	0.207	0.426***	7.937***	8.165***	0.219	-0.005	-0.293	-0.187	0.239	0.044
R-square	0.149	0.144	0.242	0.092	0.528	0.493	0.333	0.459	0.143	0.136	0.035	0.058	0.477	0.523	0.560	0.597
Obs.	220	547	220	547	192	485	192	485	730	670	730	670	571	599	571	599
Bank fixed effect	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no
Robust error	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

* Statistically significant at 10% level.
** Statistically significant at 5% level.
*** Statistically significant at 1% level.

Reference

Adams, B., Carow, K.A. and Perry, T. (2009). Earnings management and initial public offerings: The case of the depository industry. *Journal of Banking & Finance*, 33(12), pp.2363–2372.

Ahmed, A.S., Takeda, C. and Thomas, S. (1998). Bank loan loss provisions: A reexamination of capital management, earnings management and signaling effects. *Journal of Accounting and Economics*, 28(1), pp.1–25.

Alali, F. and Jaggi, B. (2011). Earnings versus capital ratios management: Role of bank types and SFAS 114. *Review of Quantitative Finance and Accounting*, 36(1), pp.105–132.

Alam, I.M.S. and Sickles, R.C.S. (1998). The Relationship Between Stock Market Returns and Technical Efficiency Innovations: Evidence from the US Airline Industry. *Journal of Productivity Analysis*, 9, pp.35–51.

Ali, A. and Zhang, W. (2015). CEO tenure and earnings management. *Journal of Accounting and Economics*, 59(1), pp.60–79.

Andreou, P.C., Philip, D. and Robejsek, P. (2016). Bank Liquidity Creation and Risk-Taking: Does Managerial Ability Matter? *Journal of Business Finance and Accounting*, 43(1–2), pp.226–259.

Anh, N. and Linh, N. (2016). Using the M-score Model in Detecting Earnings Management : Evidence from Non-Financial Vietnamese Listed Companies. *VNU Journal of Science: Economics and Business*, 32(2), pp.14–23.

Arellano, M. and Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, 68(1), pp.29–51.

Asmild, M. and Zhu, M. (2016). Controlling for the use of extreme weights in bank efficiency assessments during the financial crisis. *European Journal of Operational Research*, 251(3), pp.999–1015.

Baik, B. et al. (2013). Changes in operational efficiency and firm performance: A frontier analysis approach. *Contemporary Accounting Research*, 30(3), pp.996–1026.

Baik, B., Farber, D.B. and Lee, S.S. (2011). CEO Ability and Management Earnings Forecasts. *Contemporary Accounting Research*, 28(5), pp.1645–1668.

Bakoush, M., Abouarab, R. and Wolfe, S. (2018). Disentangling the impact of securitization on bank profitability. *Research in International Business and Finance*, 47(September 2018), pp.519–537.

Baltagi, B.H. and Wu, P.X. (1999). Unequally Spaced Panel Data Regressions With Ar(1) Disturbances. *Econometric Theory*, 15(6), pp.814–823.

Banna, H., Ahmad, R. and Koh, E.H.Y. (2018). How does total quality management influence the loan quality of the bank? *Total Quality Management and Business Excellence*, 29(3–4), pp.287–300.

Barr, R.S., Seiford, L.M. and Siems, T.F. (1993). Managerial Efficiency of Banks. *Annals of Operations Research*, 45, pp.1–19.

Reference

Barth, J.R. et al. (2013). Do bank regulation, supervision and monitoring enhance or impede bank efficiency? *Journal of Banking and Finance*, 37(8), pp.2879–2892.

Barth, M.E. et al. (2017). Bank earnings and regulatory capital management using available for sale securities. *Review of Accounting Studies*, 22(4), pp.1761–1792.

Barton, J. and Simko, P.J. (2002). The Balance Sheet as an Earnings. *The Accounting Review*, 77(Supplement), pp.1–27.

Beatty, A. and Harris, D.G. (1998). The Effects of Taxes , Agency Costs and Information Asymmetry on Earnings Management : A Comparison of Public and Private Firms. *Review of Accounting Studies*, 2, pp.299–326.

Beatty, A. and Liao, S. (2011). Do delays in expected loss recognition affect banks' willingness to lend? *Journal of Accounting and Economics*, 52(1), pp.1–20.

Beatty, A.L. et al. (2002). Earnings Management to Avoid Earnings Declines across Publicly and Privately Held Banks. *The Accounting Review*, 77(3), pp.547–570.

Beaver, W. et al. (1989). Financial Reporting, Supplemental Disclosures, and Bank Share Prices. *Journal of Accounting Research*, 27, pp.157–178.

Beaver, W.H. and Engel, E.E. (1996). Discretionary behavior with respect to allowances for loan losses and the behavior of security prices. *Journal of Accounting and Economics*, 22(1–3), pp.177–206.

Becker, C.L. et al. (1998). The Effect of Audit Quality on Earnings Management. *Contemporary Accounting Research*, 15(1), pp.1–24.

Behr, A. (2010). Quantile regression for robust bank efficiency score estimation. *European Journal of Operational Research*, 200(2), pp.568–581.

Beneish, M.D. (1999). The Detection of Earnings Manipulation. *Financial Analyst Journal*, 55(5), pp.24–36.

Beneish, M.D., Lee, C.M.C. and Nichols, D.C. (2013). Earnings manipulation and expected returns. *Financial Analysts Journal*, 69(2), pp.57–82.

Bergbrant, M.C. and Hunter, D.M. (2018). (How) do credit market conditions affect fi rms ' post-hedging outcomes ? Evidence from bank lending standards and fi rms ' currency exposure ☆. *Journal of Corporate Finance*, 50, pp.203–222.

Berger, A.N. et al. (2005). Does function follow organizational form ? Evidence from the lending practices of large and small banks $. *Journal of Financial Economics*, 76(2), pp.237–269.

Berger, A.N., Makaew, T. and Roman, R.A. (2019). Do Business Borrowers Benefit from Bank Bailouts?: The Effects of TARP on Loan Contract Terms. *Financial Management*, 48(2), pp.575–639.

Berger, A.N. and Roman, R.A. (2017). Did Saving Wall Street Really Save Main Street? The Real Effects of TARP on Local Economic Conditions. *Journal of Financial and Quantitative Analysis*, 52(5), pp.1827–1867.

Berger, A.N. and Roman, R.A. (2015). Did TARP Banks Get Competitive Advantages? *Journal of financial and quantitative analysis*, 50(6), pp.1199–1236.

Reference

Bernanke, B.S. and Blinder, A.S. (1992). The Federal Funds Rate and the Channels of Monetary Transmission. *American Economic Review*, 82, pp.901–921.

Biddle, G.C., Ma, M.L.Z. and Song, F.M. (2016). Accounting Conservatism and Bankruptcy Risk. *SSRN Electronic Journal*.

Black, L.K. and Hazelwood, L.N. (2013). The effect of TARP on bank risk-taking. *Journal of Financial Stability*, 9(4), pp.790–803.

Blankley, A.I., Comprix, J. and Hong, K.P. (2013). Earnings management and the allocation of net periodic pension costs to interim periods. *Advances in Accounting*, 29(1), pp.27–35.

Boeker, W. (1997). Stragetic Change: The Influence of Managerial Characteristics and Organizational Growth. *The Academy of Management Journal*, 40(1), pp.152–170.

Borgen, N.T. (2018). Fixed Effects in Unconditional Quantile Regression. *The Stata Journal: Promoting communications on statistics and Stata*, 16(2), pp.403–415.

Burgstahler, D. and Dichev, I. (1997). Earnings Management to Avoid Earnings Decreases and Losses. *Journal of Accounting and Economics*, 24(1), pp.99–126.

Burgstahler, D.C., Hail, L. and Leuz, C. (2006). The importance of reporting incentives: Earnings management in European private and public firms. *Accounting Review*, 81(5), pp.983–1016.

Bushman, R., Engel, E. and Smith, A. (2006). An analysis of the relation between the stewardship and valuation roles of earnings. *Journal of Accounting Research*, 44(1), pp.53–83.

Butler, A.W., Connor, M.O. and Kieschnick, R. (2014). Robust determinants of IPO underpricing and their implications for IPO research ☆*Journal of Corporate Finance*, 27, pp.367–383.

Calabrese, R., Degl'Innocenti, M. and Osmetti, S.A. (2017). The effectiveness of TARP-CPP on the US banking industry: A new copula-based approach. *European Journal of Operational Research*, 256(3), pp.1029–1037.

Campa, D. and Hajbaba, A. (2016). Do targets grab the cash in takeovers: The role of earnings management. *International Review of Financial Analysis*, 44, pp.56–64.

Carter, D.A. and Mcnulty, J.E. (2005). Deregulation , technological change , and the business-lending performance of large and small banks. *Journal of Banking & Finance*, 29(5), pp.1113–1130.

Cassell, C.A., Myers, L.A. and Seidel, T.A. (2015). Disclosure transparency about activity in valuation allowance and reserve accounts and accruals-based earnings management. *Accounting, Organizations and Society*, 46, pp.23–38.

Chahine, S., Mansi, S. and Mazboudi, M. (2015). Media news and earnings management prior to equity offerings. *Journal of Corporate Finance*, 35, pp.177–195.

Chang, J.C. and Sun, H.-L. (2009). Crossed-listed foreign firms' earnings informativeness, earnings management and disclosures of corporate governance information under SOX. *The International Journal of Accounting*, 44(1), pp.1–32.

Reference

Chemmanur, T.J. and Paeglis, I. (2005). Management quality, certification, and initial public offerings. *Journal of Financial Economics*, 76(2), pp.331–368.

Chen, C. et al. (2012). Idiosyncratic Return Volatility and the Information Quality Underlying Managerial Discretion. *Journal of Financial and Quantitative Analysis*, 47(4), pp.873–899.

Chen, C., Kim, J.B. and Yao, L. (2017). Earnings smoothing: Does it exacerbate or constrain stock price crash risk? *Journal of Corporate Finance*, 42, pp.36–54.

Chen, S.-S. et al. (2013). Information Uncertainty, Earnings Management, and Long-run Stock Performance Following Initial Public Offerings. *Journal of Business Finance & Accounting*, 40(9–10), pp.1126–1154.

Chen, S.K. et al. (2010). The frequency and magnitude of earnings management: Time-series and multi-threshold comparisons. *International Review of Economics & Finance*, 19(4), pp.671–685.

Cheng, Q., Warfield, T. and Ye, M. (2011). Equity incentives and earnings management: Evidence from the Banking Industry. *Journal of Accounting, Auditing and Finance*, 26(2), pp.317–349.

Chih, H.L., Shen, C.H. and Kang, F.C. (2008). Corporate social responsibility, investor protection, and earnings management: Some international evidence. *Journal of Business Ethics*, 79(1–2), pp.179–198.

Cho, S.H., Loibl, C. and Geistfeld, L. (2014). Motivation for emergency and retirement saving: An examination of Regulatory Focus Theory. *International Journal of Consumer Studies*, 38(6), pp.701–711.

Chronopoulos, D.K. et al. (2015). The dynamics of US bank profitability. *European Journal of Finance*, 21(5), pp.426–443.

Coelli, T. (1998). A multi-stage methodology for the solution of orientated DEA models. *Operations Research Letters*, 23(3–5), pp.143–149.

Cohen, D.A., Dey, A. and Lys, T.Z. (2008). Real and Accrual- Based Earnings Management in the Pre- and Post- Sarban. *The Accounting Review*, 83(3), pp.757–787.

Cohen, D.A. and Zarowin, P. (2010). Accrual-based and real earnings management activities around seasoned equity offerings. *Journal of Accounting and Economics*, 50(1), pp.2–19.

Cohen, L. et al. (2014). Bank Earnings Management and Tail Risk during the Financial Crisis. *Journal of Money, Credit and Banking*, 46(1), pp.171–197.

Contessi, S., De Pace, P. and Guidolin, M. (2020). Mildly explosive dynamics in U.S. fixed income markets. *European Journal of Operational Research*, 287, pp.712–724.

Cornett, M.M., McNutt, J.J. and Tehranian, H. (2009). Corporate governance and earnings management at large U.S. bank holding companies. *Journal of Corporate Finance*, 15(4), pp.412–430.

Cyert, R.M. and March, J.G. (1963). *A Behavioral Theory of the Firm*. Cliffs Englewood, NJ: Prentice Hall.

Reference

Davila, E. and Walther, A. (2019). Does Size Matter ? Bailouts with Large and Small. *Journal of Financial Economics*.

DeAngelo, L. (2020). Discussion of Evidence of Earnings Management from the Provision for Bad Debts. *Journal of Accounting Research*, 26(1988), pp.32–40.

Dechow, P.M., Kothari, S.P. and Watts, R.L. (1998). The relation between earnings and cash. *Journal of Accounting and Economics*, 25, pp.133–168.

Degeorge, F., Patel, J. and Zeckhauser, R. (1999). Earnings management to exceed thresholds. *The Journal of Business*, 72(1), pp.1–33.

Delis, M.D., Iosifidi, M. and Tsionas, M. (2020). Management estimation in banking. *European Journal of Operational Research*, 284(1), pp.355–372.

Demerjian, P.R. et al. (2013). Managerial ability and earnings quality. *Accounting Review*, 88(2), pp.463–498.

Demerjian, P.R., Lev, B. and McVay, S.E. (2012). Quantifying Managerial Ability: A New Measure and Validity Tests. *Management Science*, 58(7), pp.1229–1248.

Demirtas, K.O. and Rodgers Cornaggia, K. (2013). Initial credit ratings and earnings management. *Review of Financial Economics*, 22(4), pp.135–145.

Demsetz, R.S. and Strahan, P.E. (1997). Diversification, Size, and Risk at Bank Holding Companies. *Journal of Money, Credit and Banking*, 29(3), p.300.

Ding, D. and Sickles, R.C. (2018). Frontier efficiency, capital structure, and portfolio risk: An empirical analysis of U.S. banks. *BRQ Business Research Quarterly*, 21(4), pp.262–277.

Dong, M. and Zhang, X.J. (2018). Selective Trading of Available-for-Sale Securities: Evidence from U.S. Commercial Banks. *European Accounting Review*, 27(3), pp.467–493.

Du, Q. and Shen, R. (2018). Peer Performance and Earnings Management. *Journal of Banking & Finance*, 89, pp.125–137.

Dye, R.A. (1988). Earnings Management in an Overlapping Generations Model. *Journal of Accounting Research*, 26(2), p.195.

Enomoto, M., Kimura, F. and Yamaguchi, T. (2015). Accrual-based and real earnings management: An international comparison for investor protection. *Journal of Contemporary Accounting and Economics*, 11(3), pp.183–198.

Erevelles, S., Horton, V. and Fukawa, N. (2007). Imagination in marketing. *Marketing Management Journal*, 17(2), pp.109–119.

Erickson, M. and Wang, S.W. (1999). Earnings management by acquiring firms in stock for stock mergers. *Journal of Accounting and Economics*, 27(2), pp.149–176.

Fan, Y. et al. (2020). Watch out for bailout: TARP and bank earnings management. *Journal of Financial Stability*, 51(March 2009), p.100785.

Farruggio, C., Michalak, T.C. and Uhde, A. (2013). The light and dark side of TARP. *Journal of Banking and Finance*, 37(7), pp.2586–2604.

Reference

Fields, L.P. et al. (2018). Refinancing pressure and earnings management: Evidence from changes in short-term debt and discretionary accruals. *Finance Research Letters*, 25, pp.62–68.

De Franco, G., Hope, O.K. and Lu, H. (2017). Managerial ability and bank-loan pricing. *Journal of Business Finance and Accounting*, 44(9–10), pp.1315–1337.

Franco, M. (1997). Risk-Adjusted Performance. *The Journal of Portfolio Management*, 23(2), pp.45–54.

Fransen, M.L. and ter Hoeven, C.L. (2011). Matching the Message: The Role of Regulatory Fit in Negative Managerial Communication. *Communication Research*, 40(6), pp.818–837.

Franz, D.R., HassabElnaby, H.R. and Lobo, G.J. (2014). Impact of proximity to debt covenant violation on earnings management. *Review of Accounting Studies*, 19(1), pp.473–505.

Fries, S. et al. (2006). Market entry, privatization and bank performance in transition. *Economics of Transition*, 14(4), pp.579–610.

Gamache, D.L. et al. (2015). Motivated to acquire? the impact of CEO regulatory focus on firm acquisitions. *Academy of Management Journal*, 58(4), pp.1261–1282.

García-Meca, E. and García-Sánchez, I.M. (2018). Does managerial ability influence the quality of financial reporting? *European Management Journal*, 36(4), pp.544–557.

Garel, A. et al. (2021). Institutional investor distraction and earnings management. *Journal of Corporate Finance*, 66(April 2020), p.101801.

Ghosh, A. (2015). Banking-industry specific and regional economic determinants of non-performing loans: Evidence from US states. *Journal of Financial Stability*, 20, pp.93–104.

Gianni, de N. (2001). Size, Charter Value and Risk in Banking: An International Perspective. *SSRN Electronic Journal*.

Gong, G., Louis, H. and Sun, A.X. (2008). Earnings Management and Firm Performance Following Open-Market Repurchases. *The Journal of Finance*, 63(2), pp.947–986.

Greene, W.H. and Segal, D. (2004). Profitability and efficiency in the U.S. life insurance industry. *Journal of Productivity Analysis*, 21(3), pp.229–247.

Guay, W.R., Kothari, S.P. and Watts, R.L. (1996). A Market-Based Evaluation of Discretionary Accrual Models. *Journal of Accounting Research*, 34(1996), pp.83–105.

Guidry, F., Leone, A.J. and Rock, S. (1999). Earnings-based bonus plans and earnings management by business-unit managers. *Journal of Accounting and Economics*, 26(1–3), pp.113–142.

Gunny, K.A. (2010). The relation between earnings management using real activities manipulation and future performance: Evidence from meeting earnings benchmarks. *Contemporary Accounting Research*, 27(3), pp.855–888.

Guo, J. et al. (2015). Foreign Ownership and Real Earnings Management: Evidence from Japan. *Journal of International Accounting Research*, 14(2), pp.185–213.

Reference

Gupta, P., Mallick, S. and Mishra, T. (2018). Does social identity matter in individual alienation ? Household-level evidence in post-reform India. *World Development*, 104, pp.154–172.

Hambrick, D.C. and Mason, P.A. (1984). The Organization as a Reflection of Its Top Managers. *Academy of Management Review*, 9(2), pp.193–206.

Harris, O., Huerta, D. and Ngo, T. (2013). The impact of TARP on bank efficiency. *Journal of International Financial Markets, Institutions and Money*, 24(1), pp.85–104.

Harris, O., Karl, J.B. and Lawrence, E. (2019). CEO compensation and earnings management: Does gender really matters? *Journal of Business Research*, 98(January), pp.1–14.

Hazarika, S., Karpoff, J.M. and Nahata, R. (2012). Internal corporate governance, CEO turnover, and earnings management. *Journal of Financial Economics*, 104(1), pp.44–69.

Healy, P.M. (1985). The effect of bonus schemes on accounting decisions. *Journal of Accounting and Economics*, 7(1–3), pp.85–107.

Heckman, J.J. (1976). The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. *Annals of Economic and Social Measurement*, 5(4), pp.475–492.

Higgins, E.T. (1997). Beyond pleasure and pain. *American Psychologist*, 52(12), pp.1280–1300.

Higgins, E.T. (2000). Making a good decision: Value from fit. *American Psychologist*, 55(11), pp.1217–1230.

Hoffmann, P.S. (2011). Determinants of the Profitability of the US Banking Industry. *International Journal of Business and Social Science*, 2(22), pp.255–269.

Hoshi, T. and Kashyap, A.K. (2010). Will the U.S. bank recapitalization succeed? Eight lessons from Japan. *Journal of Financial Economics*, 97(3), pp.398–417.

Hossain, M. et al. (2011). Corporate governance and earnings management in the Pre- and Post-sarbanes-oxley act regimes: Evidence from implicated option backdating firms. *Journal of Accounting, Auditing and Finance*, 26(2), pp.279–315.

Huang, K., Lao, B. and McPhee, G. (2017). Does Stock Liquidity Affect Accrual-based Earnings Management? *Journal of Business Finance and Accounting*, 44(3–4), pp.417–447.

Humphrey, D.B. and Pulley, L.B. (1997). Banks ' Responses to Deregulation : Profits , Technology , and Efficiency. *Journal of Money, Credit and Banking*, 29(1), pp.73–93.

Jang, K.Y. (2017). The effect of TARP on the propagation of real estate shocks: Evidence from geographically diversified banks. *Journal of Banking and Finance*, 83, pp.173–192.

Jaskiewicz, P. and Luchak, A.A. (2013). Explaining performance differences between family firms with family and nonfamily CEOs: It's the nature of the tie to the family that counts! *Entrepreneurship: Theory and Practice*, 37(6), pp.1361–1367.

Jensen, M.C. (1968). The performance of mutual funds in the period 1945-1964. *Journal of Finance*, 23(2), pp.389–416.

Reference

Jiang, C., Kanas, A. and Molyneux, P. (2018). Public policy and financial stability: The impact of PCA and TARP on U.S. bank non-performing loans. *International Journal of Finance and Economics*, 23(4), pp.376–392.

Jin, J.Y. et al. (2013). Impact of FDICIA internal controls on bank risk taking. *Journal of Banking and Finance*, 37(2), pp.614–624.

Jones, J.J. (1991). Earnings Management During Import Relief Investigations. *Journal of Accounting Research*, 29(2), p.193.

Kanagaretnam, K., Lim, C.Y. and Lobo, G.J. (2010). Auditor reputation and earnings management: International evidence from the banking industry. *Journal of Banking and Finance*, 34(10), pp.2318–2327.

Kanagaretnam, K., Lobo, G.J. and Mathieu, R. (2004). Earnings Management to Reduce Earnings Variability: Evidence from Bank Loan Loss Provisions. *Review of Accounting and Finance*, 3(1), pp.128–148.

Khan, A.R. and Akter, M. (2017). An Analysis of Earnings Management: Evidence from Food & Allied Industry of Bangladesh. *International Journal of Accounting and Financial Reporting*, 7(2), p.359.

Kim, I. et al. (2016). Drivers behind the monitoring effectiveness of global institutional investors: Evidence from earnings management. *Journal of Corporate Finance*, 40, pp.24–46.

Kim, J., Lee, C.Y. and Cho, Y. (2016). Technological diversification, core-technology competence, and firm growth. *Research Policy*, 45(1), pp.113–124.

Köster, H. and Pelster, M. (2017). Financial penalties and bank performance. *Journal of Banking and Finance*, 79, pp.57–73.

Kothari, S.P. (2001). Capital markets research in accounting. *Journal of Accounting and Economics*, 31, pp.105–231.

Laverty, K.J. (1996). Economic " Short-Termism ": The Debate , the Unresolved Issues , and the Implications for Management Practice and Research. , 21(3), pp.825–860.

Lee, C.C. et al. (2018). Managerial ability and corporate investment opportunity. *International Review of Financial Analysis*, 57(February), pp.65–76.

Leuz, C., Nanda, D. and Wysocki, P.D. (2003). Earnings management and investor protection: An international comparison. *Journal of Financial Economics*, 69(3), pp.505–527.

Leverty, J.T. and Grace, M.F. (2012). Dupes or Incompetents? An Examination of Management's Impact on Firm Distress. *Journal of Risk and Insurance*, 79(3), pp.751–783.

Li, L. (2013). TARP funds distribution and bank loan supply. *Journal of Banking and Finance*, 37(12), pp.4777–4792.

Li, L., Ma, M. and Song, V. (2018). Client importance, bank risk, and systemic risk. *Asian Review of Accounting*, 26(4), pp.511–544.

Li, X. (2010). Real Earnings Management and Subsequent Stock Returns. *SSRN Electronic*

Journal.

Liao, Z. and Long, S. (2018). CEOs' regulatory focus, slack resources and firms' environmental innovation. *Corporate Social Responsibility and Environmental Management*, 25(5), pp.981–990.

Liu, Q. and Lu, Z. (Joe). (2007). Corporate governance and earnings management in the Chinese listed companies: A tunneling perspective. *Journal of Corporate Finance*, 13(5), pp.881–906.

Lobo, G.J. and Yang, D.H. (2001). Bank Managers' Heterogeneous Decisions on Discretionary Loan Loss Provisions. *Review of Quantitative Finance and Accounting*, 16(3), pp.223–250.

Loewenstein, G. and Prelec, D. (1992). Anomalies in Intertemporal Choice : Evidence and an Interpretation. *The Quarterly Journal of Economics*, 107(2), pp.573–597.

Mamatzakis, E. and Bermpei, T. (2016). What is the effect of unconventional monetary policy on bank performance ? *Journal of International Money and Finance*, 67, pp.239–263.

Marks, J.M. and Musumeci, J. (2017). Misspecification in event studies. , 45, pp.333–341.

Mcnichols, M. and Wilson, G.P. (1988). Evidence of Earnings Management from the Provision for Bad Debts. *Journal of Accounting Research*, 26(1988), pp.1–31.

Meles, A. et al. (2016). The impact of intellectual capital efficiency on commercial bank performance: Evidence from the US. *Journal of Multinational Financial Management*, 36, pp.64–74.

Miller, S.M. and Noulas, A.G. (1996). The technical efficiency of large bank production. *Journal of Banking and Finance*, 20(3), pp.495–509.

Mohr, A.T. and Puck, J.F. (2007). Role Conflict, General Manager Job Satisfaction and Stress and the Performance of IJVs. *European Management Journal*, 25(1), pp.25–35.

Montgomery, H. and Takahashi, Y. (2014). The economic consequences of the TARP: The effectiveness of bank recapitalization policies in the U.S. *Japan and the World Economy*, 32, pp.49–64.

Morris, R.D., Kang, H. and Jie, J. (2016). The determinants and value relevance of banks' discretionary loan loss provisions during the financial crisis. *Journal of Contemporary Accounting and Economics*, 12(2), pp.176–190.

Moses, O.D. (1987). Income smoothing and incentives: empirical tests using accouting changes. *The Accounting Review*, 62(2), pp.358–377.

Nwaeze, E., Xu, Q. and Yin, Q.J. (2018). The implications of TARP: Evidence from bank performance and CEO pension benefits. *Journal of Accounting and Public Policy*, 37(5), pp.458–476.

Park, K.E. (2017). Earnings quality and short selling: Evidence from real earnings management in the United States. *Journal of Business Finance and Accounting*, 44(9–10), pp.1214–1240.

Peni, E. and Vähämaa, S. (2010). Female executives and earnings management.

Managerial Finance, 36(7), pp.629–645.

Perotti, P. and Windisch, D. (2017). Managerial Discretion in Accruals and Informational Efficiency. *Journal of Business Finance and Accounting*, 44(3–4), pp.375–416.

Perry, S.E. and Williams, T.H. (1994). Earnings management preceding management buyout offers. *Journal of Accounting and Economics*, 18(2), pp.157–179.

Pope, P.F., Peasnell, K. V. and Young, S. (1998). Outside Directors, Board Effectiveness, and Earnings Management. *SSRN Electronic Journal*.

Pourciau, S. (1993). Earnings management and nonroutine executive changes. *Journal of Accounting and Economics*, 16(1–3), pp.317–336.

Quaranta, A.G., Raffoni, A. and Visani, F. (2018). A multidimensional approach to measuring bank branch efficiency. *European Journal of Operational Research*, 266(2), pp.746–760.

Rangan, S. (1998). Earnings management and the performance of seasoned equity offerings. *Journal of Financial Economics*, 50(1), pp.101–122.

Roychowdhury, S. (2006). Earnings management through real activities manipulation. *Journal of Accounting and Economics*, 42(3), pp.335–370.

Sarkar, J., Sarkar, S. and Sen, K. (2008). Board of directors and opportunistic earnings management: Evidence from India. *Journal of Accounting, Auditing and Finance*, 23(4), pp.517–551.

Schelling, T.C. (2016). Self-Command in Practice , in Policy , and in a Theory of Rational Choice. *American Economic Association*, 74(2), pp.1–11.

Semaan, E. and Drake, P.P. (2016). TARP and the long-term perception of risk. *Journal of Banking and Finance*, 68, pp.216–235.

Sharpe, W.F. (1994). The Sharpe Ratio. *The Journal of Portfolio Management*, 21(1), pp.49–58.

Shen, C.H. and Huang, Y.L. (2013). Effects of earnings management on bank cost of debt. *Accounting and Finance*, 53(1), pp.265–300.

Silva, T.C. et al. (2017). A comparison of DEA and SFA using micro- and macro-level perspectives: Efficiency of Chinese local banks. *Physica A: Statistical Mechanics and its Applications*, 469, pp.216–223.

Sloan, R.G. (1996). Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings? *The Accounting Review*, 71(3), pp.289–315.

Song, W.L. and Uzmanoglu, C. (2016). TARP announcement, bank health, and borrowers' credit risk. *Journal of Financial Stability*, 22, pp.22–32.

El Sood, H.A. (2012). Loan loss provisioning and income smoothing in US banks pre and post the financial crisis. *International Review of Financial Analysis*, 25, pp.64–72.

Spokeviciute, L., Keasey, K. and Vallascas, F. (2019). Do financial crises cleanse the banking industry? Evidence from US commercial bank exits. *Journal of Banking and Finance*, 99, pp.222–236.

Reference

Stever, R. (2007). Bank size , credit and the sources of bank market risk. *SSRN Electronic Journal*.

Subramanyam, K.R. (1996). The pricing of discretionary accruals. *Journal of Accounting and Economics*, 22, pp.249–281.

Teoh, S., Ivo, W. and Wong, T.. (1998). Earnings Management and the Long-Run Market Performance of Initial Public Offerings. *The Journal of Finance*, 53(6), pp.1935–1974.

Teoh, S.H., Welch, I. and Wong, T.J. (1998). Earnings management and the underperformance of seasoned equity offerings. *Journal of Financial Economics*, 50(1), pp.63–99.

Tsionas, M.G. and Mamatzakis, E. (2019). Further results on estimating inefficiency effects in stochastic frontier models. *European Journal of Operational Research*, 275(3), pp.1157–1164.

Vorst, P. (2016). Real Earnings Management and Long-Term Operating Performance: The Role of Reversals in Discretionary Investment Cuts. *The Accounting Review*, 91(4), pp.1219–1256.

Wahlen, J.M. (1994). The Nature of Information Bank Loan in Commercial Loss Disclosures. *The Accounting Review*, 69(3), pp.455–478.

Wang, C. (2013). Bailouts and bank runs: Theory and evidence from TARP. *European Economic Review*, 64, pp.169–180.

Wanke, P., Barros, C.P. and Emrouznejad, A. (2016). Assessing productive efficiency of banks using integrated Fuzzy-DEA and bootstrapping: A case of Mozambican banks. *European Journal of Operational Research*, 249(1), pp.378–389.

Warfield, T.D., Wild, J.J. and Wild, K.L. (1995). Managerial ownership, accounting choices, and informativeness of earnings. *Journal of Accounting and Economics*, 20(1), pp.61–91.

Wheelock, D.C. and Wilson, P.W. (2000). Why Do Banks Disappear? The Determinants of U.S. Bank Failures and Acquisitions. *The Review of Economics and Statistics*, 82(1), pp.127–128.

Xie, H. (2001). The Mispricing of Abnormal Accruals. *Accounting Review*, 76(3), p.357.

Yang, T.-H., Hsu, J. and Yang, W.-B. (2016). Firm’s motives behind SEOs, earnings management, and performance. *International Review of Economics & Finance*, 43, pp.160–169.

Yung, K. and Root, A. (2019). Policy uncertainty and earnings management: International evidence. *Journal of Business Research*, 100(April 2018), pp.255–267.

Zang, A.Y. (2012). Evidence on the trade-off between real activities manipulation and accrual-based earnings management. *Accounting Review*, 87(2), pp.675–703.